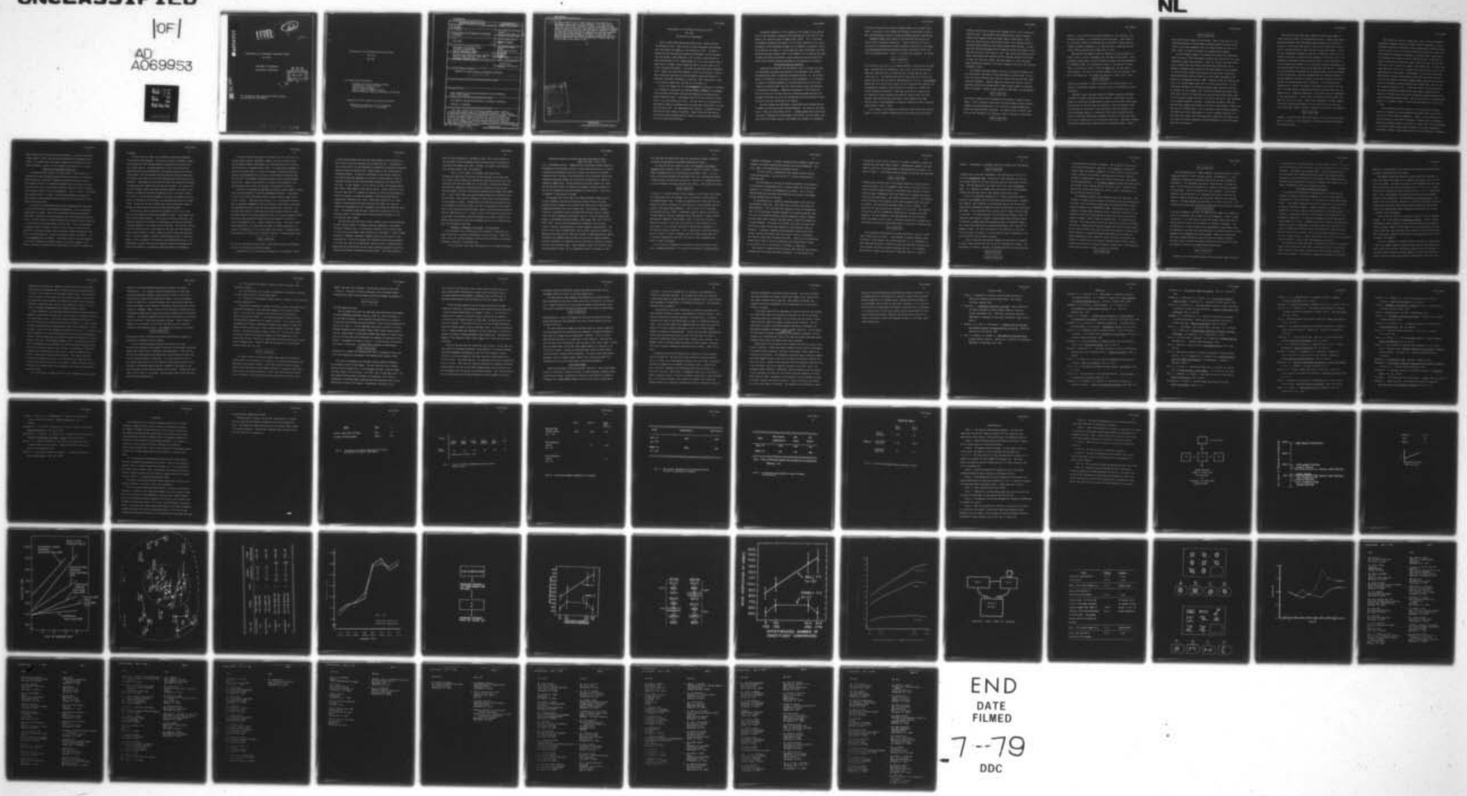
AD-A069 953 WASHINGTON UNIV SEATTLE DEPT OF PSYCHOLOGY F/G 5/10
INTELLIGENCE AS AN INFORMATION PROCESSING CONCEPT.(U)
MAY 79 E HUNT N00014-77-C-0225

UNCLASSIFIED NL

1 OF 1

AD
A069953



END
DATE
FILMED
7--79
DDC

Intelligence as an Information Processing Concept

Earl Hunt

Department of Psychology

University of Washington

Intelligence as an Information Processing Concept

Earl Hunt

May 1979

This research was sponsored by:

Personnel and Training Research Programs
Psychological Sciences Division
Office of Naval Research
Under Contract No. N00014-77-C-0225
Contract Authority Identification Number, NR 154-398

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER NR 154-398-5	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) 6 Intelligence as an Information Processing Concept		5. TYPE OF REPORT & PERIOD COVERED Interim April 1, 1978 -March 31, 1979
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) 10 Earl Hunt		8. CONTRACT OR GRANT NUMBER(s) 15 N00014-77-C-0225
9. PERFORMING ORGANIZATION NAME AND ADDRESS Department of Psychology NI-25 University of Washington Seattle, Washington 98195		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS 61153N RR 042-06;RR 042-06-01 NR 154-398
11. CONTROLLING OFFICE NAME AND ADDRESS Personnel and Training Research Programs Office of Naval Research (Code 458) Arlington, Virginia 22217		12. REPORT DATE 11 May 1979
		13. NUMBER OF PAGES 37 12 74p
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office) 9 Interim rept. 1 Apr 78 - 31 Mar 79		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited

16 RR04206 17 RR0420601

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

Paper presented at British Psychological Society Conference, April, 1979, England.

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

intelligence, information processing, individual differences,

attention, strategies

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This paper examines the relationship between general cognitive competence and several aspects of information processing. Three sources of individual differences in information processing are proposed: structure, strategy, and general attentional resources. Structural factors set limits on the effectiveness of specific information processing steps. These factors appear to be important when we contrast the cognitive capacities of extreme groups, such as normal and mentally retarded persons

(over)

DD FORM 1 JAN 73 1473 EDITION OF 1 NOV 65 IS OBSOLETE
S/N 0102 LF 014 6601

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

387 783

UNCLASSIFIED

SECURITY CLASSIFICATION OF THIS PAGE(When Data Entered)

(cont)

but they account for only a small amount of the variability in homogeneous groups such as college students. The reason may be that within such groups, strategy of attacking problems is a more important source of variation, and moderates the relationship between simple information processing steps and complex reasoning. Finally, the fact that scores on almost all measures of cognitive competence are positively correlated may be related to the fact that all mental processes seem to compete for general attentional resources, and that individuals differ in the attentional resources they can bring to bear on any cognitive task.

Accession For	
NTIS GRA&I	✓
DDC TAB	
Unannounced	
Justification	
By	
Distribution/	
Availability Codes	
Dist	Avail and/or special
A	

UNCLASSIFIED

SECURITY CLASSIFICATION OF THIS PAGE(When Data Entered)

Intelligence as an Information Processing Concept*

Earl Hunt

The University of Washington

My son's high school biology text begins with a chapter entitled "The meaning of life." After he and his fellow teen-agers have mastered this, they move on to Chapter 2, "The diversity of life." Is there a message here for those who would explain intelligence? How can we speak about who thinks, or who thinks well, until we have a clear picture of what thinking means to us? Viewed another way, if we think that we have a good theory of thought, then we should be able to use that theory to describe individual differences. This point has been made before (Underwood, 1975). Rather than repeat the argument, I shall try to develop it further. What progress has been made by using information processing theories to understand individual differences in cognition? More interestingly, where is our progress stymied, why, and what can we do about it?

A naive, but common, way of studying individual differences in cognition is to establish a statistical relationship between performance on psychometrically defined intelligence tests and performance on more theoretically defined laboratory tasks. Investigators who do this are usually not interested in the intelligence test itself. The test serves as a surrogate for some general cognitive performance that has been shown, empirically, to correlate with test score. The experimental task, however, is supposed to have been derived from a theory of cognition. Hence linking the test and the task should provide evidence that our theories of cognition have something to do with natural world thinking.

A prominent subspecies of this approach is the attempt to link performance on tests designed to evaluate verbal aptitude with tasks that are supposed to tap some pure aspect of memory (Hunt, 1978a). This is an attractive endeavor because of the central role of verbal processes in our culture and because of the prominence of memory in our theories of cognition. While the purpose of this paper is to raise questions about intelligence and information processing in general, most of the examples will be based on the study of memory and verbal intelligence, simply because we know more about this point on the interface between psychometrics and experimental psychology.

The Current Status of the Effort

Saying that the approach just described is naive is perhaps too harsh. The experimental paradigms used typically yield parameters that estimate some theoretically basic information processing function, e.g. the speed of access to information in either short or long term memory. It is certainly of interest to determine whether or not those people who are facile with linguistic reasoning differ from less facile persons along such dimensions of information processing. Indeed one of Underwood's (1975) points was that the failure to find that there are differences between more and less competent individuals on any of our information processing parameters should be cause for serious rethinking of our theories.

How much progress has been made in establishing links between theories of memory and individual verbal aptitude measures? The answer to this question is "Some, but surprisingly little." A common problem keeps resurfacing; very small differences are found between "high verbal" and "low verbal" subjects within the normal range of intelligence, but substantial differences

are found if we move to the study of extreme groups, such as mental retardates. To see this, let us examine the findings in three areas; access to well learned material, access to recently presented material, and learning.

Asymptotic memory access refers to the speed with which we can retrieve highly overlearned associations. A useful technique for testing the speed of an asymptotically learned lingusitic association is the stimulus identification paradigm developed by Posner and Mitchell (1967), and since used by many others. Figure 1 illustrates the procedure. Two letters

---

Figure 1 about here

---

are presented, and the task is to indicate whetehr or not they have the same name. Concentrating our attention on "yes" trials, letters may be either physically identical (PI), as in the pair A-A, or name identical (NI), as in the pair A-a. The reaction time (RT) for identification of NI pairs is greater than the reaction time for identification of PI pairs. The difference between RTs for NI and PI pairs, which will be called the NI-PI measure, can be regarded as a measure of the efficiency of retrieval of a highly overlearned linguistic association.[1] Note that using the NI-PI measure does not commit one to the assumption that physical identification inevitably precedes name identification, but simply to the assumption that name identification is more dependent on linguistic associations than is physical identification. (Posner, 1978).

Since reading is the process of associating verbal codes with arbitrary symbols, one can reasonably hypothesize that the naming process should be

related to the ability to use written language, which is what a verbal aptitude test tests. The hypothesis fares moderately well when we examine studies using subjects within the normal range of intelligence. Table 1 shows the results from two correlational studies in our laboratory, one involving college students and one involving grade school children. In both cases the correlation between the NI-PI measure and the intelligence or aptitude test score was on the order of -.30.[2] Such results are consistent with results from studies that contrast the NI-PI measures obtained from groups of "high" and "low" test scorers, when both groups are within the normal range (Goldberg and Schwartz, 1977; Hunt, Lunneborg, and Lewis, 1975; Keating and Bobbitt, 1978).

We can make a much more dramatic case for an association between "verbal intelligence" and access to long term memory for verbal codes if we contrast the results obtained from studies of groups that span the whole range of mental competence. Figure 2 summarizes several such studies, covering populations ranging from exceptionally bright college students to educable mental retardates. A point of some interest is that there is a considerable

Table 1 about here

non-linearity between the NI-PI measure and estimates of "general intelligence". There is roughly a thirty point IQ spread between bright university students and average young adults, and a similar IQ spread between young adults and educable mental retardates. The results shown in Figure 2 show that the equal difference in "IQ points", which is basically a statistical

Figure 2 about here

concept, is not paralleled by an equal difference in our estimates of the efficiency of memory... an information processing concept. There seems to be little prior reason for preferring one or the other of these scales as a measure of mental competence, so it would be hard to argue that the non-linear relation indicates that either scale is wrong.

When we move from speed of access of material in long term memory to speed of access in short term memory, much the same picture applies. Short term memory access speed is usually measured by memory scanning experiments, (S. Sternberg, 1966), as illustrated in Figure 3. The observer is shown from 1 to 6 letters or digits, called the memory set, and then shown a probe stimulus. The task is to indicate whether or not the probe was a member of the memory set. RT to make this decision is found to be a linear

---
Figure 3 about here

---

function of the number of items in the memory set, and the slope of this function is considered a measure of speed of access to information in short term memory.

Equivocal results have been obtained in studies examining individual differences in memory scanning in normal subjects. While there are some reports of correlations between memory scanning rate and verbal intelligence, the relations are neither large nor consistent. Chang and Atkinson (1976) even reported sex differences in the direction of the relationship! Our present knowledge supports S. Sternberg's (1975) earlier conclusion that there are individual differences in memory scan rates, but that their relation to other characteristics of the person is not clear. Once again, though, the picture changes when we examine results from extreme groups. Figure 4

Figure 4 about here
----

shows results from a number of such studies. There is more than a 10 to 1 difference between the fastest memory scanning reported (by Hunt and Love (1972), for an expert mnemonist) and the slowest reported (by Harris and Fleer (1974), for mental retardates with suspected brain damage).

A similar pattern appears if we change from studies that examine the speed of access of short term memory to studies that examine its size, using conventional memory span procedures. There are reliable individual differences in memory span that are not associated with differential use of mnemonic strategies (Lyon, 1977), but this again appears to be an example of a statistically reliable effect that is not practically significant. Normal adult memory span runs from five to nine items, depending on the material to be memorized (Miller, 1956). Matarazzo (1972) has observed that this is not a wide enough range to be of clinical significance.[3] On the other hand, Matarazzo also advises that memory spans below this range may be indicants of brain damage. Ellis (1978) has observed that mental retardates show a deficit on practically any task that taps primary memory capacity, and argues strongly that this is not due to a failure of the retardates to use powerful mnemonic strategies. Huttenlocher and Burke (1976) have made the same argument with respect to the fairly large changes in memory span that occur as children mature. As in the case of long term memory measures, the efficiency of short term memory is at best a moderate predictor of intelligence test scores within the normal adult range, but if we move to the full spectrum of mental competence, marked differences in short term memory efficiency are observed.

Over the years there have been a number of studies that attempt to relate "ability to learn" to intelligence test score. Indeed, some authors have even maintained that intelligence should be defined as the ability to learn. To the extent that there is truth in this proposition, performance in learning experiments should relate to tested intelligence. One of the most comprehensive attempts to show this relationship, almost as a by-product of an effort to understand the components of learning itself, is an experiment by Underwood, Boruch, and Malmi (1978), in which some 200 university students participated in 33 (!) different learning experiments, and also made available their scores of the Scholastic Aptitude Test. Underwood et al. were primarily interested in the factorial composition of performance on the learning tasks, and simply observed that the different subtests of the SAT appeared to represent a cluster of abilities different from those required for learning under various conditions. I have reanalyzed the Underwood et al. results, including in the analysis the aptitude test measures. A factor analysis recovered the original learning factors and, as Underwood et al. suggested, identified a "test factor" that was independent of the learning factors. Table 2 shows the loading of the SAT verbal aptitude test on all six factors. Clearly test performance in normal subjects is related to learning performance, but the relation is not a close one. On the other hand, though, learning is notoriously deficient in the mentally

----

Table 2 about here

----

retarded. It has also been found that injuries to various brain structures render it difficult, if not impossible, to learn new associations between well recognized items.

These results are typical of many other results relating information processing to general measures of (verbal) cognitive competence. Given reasonable attention to statistical power considerations, reliable associations are easy to find. Practically significant associations, within the normal range of intellectual competence, are seldom found. Keele (Note 1) has summarized the situation nicely by referring to the ".3 barrier", no single information processing task seems to able to account for more than 10 per cent of the variance in a general intelligence test. Of course, one might hope that a set of, say, ten such tasks would provide us with a complete account of intelligence. Unfortunately, this does not work either. Most measures of memory functioning are positively correlated with each other, so the multiple correlations between verbal aptitude tests and batteries of information processing measures are seldom higher than .6 (see, for instance, Lunneborg, 1977). On the other hand, as soon as we move to the study of differences between groups whose mental competence varies widely, we find that practically every information processing measure will singly differentiate between groups. What we do not find is any appreciable number of "in between" studies, in which the correlations are in the .5 to .7 range.

I do not believe that this problem is a statistical one, produced solely by a tendency to study populations who differ either very little or very much in their cognitive competence. Rather, I believe that we are seeing evidence of a qualitative difference. Changes in basic information processing parameters probably do account for a great deal of the differences in individual cognitive power when we compare, say, mental retardates to high school students. When we examine the very real differences in cognitive

power between dull and bright university students, or even dull and bright "normal people", we may find that these differences are produced by other factors. To consider what these other factors are, and how they fit into cognitive theory, a return to a more theoretical perspective is in order.

Cognition and Information Processing

Following the lead of Newell and Simon (1972), I believe that it is appropriate to think of human reasoning as being the product of a program's being executed on a peculiar information processing device, our brains. The "computer analogy" is frequently misunderstood to mean that our brains must follow the style of processing of physical computers; binary operation, passive memory systems, and serial computation. This is in error. The analogy only maintains that it is useful to think about thought by applying the same concepts to human reasoning that we would apply to any physical information processing system.

Every problem solving machine must possess some mechanistic capacities for storing, retrieving, and transforming information. This is the *structural* aspect of thought. Most of the information processing paradigms of experimental psychology have been designed to deal with structural considerations. In order to solve a problem the mechanistic capacities must be applied in a particular, and possibly highly flexible, order. This is the program, or *process*, aspect of thought. Finally, virtually every activity that we would call intelligent presumes some co-ordination between the present situation and the problem solver's store of previously acquired information. This is the *knowledge* aspect of thought. You cannot say how, or how successfully, a particular information processing system...be it man or computer...will attack a particular problem unless you understand its structure, process, and

knowledge.

To drive this point home, let us consider an analogy to basketball playing rather than computing. If you try to predict a basketball player's scoring potential from isolated physical characteristics you would have only limited success. Extreme weaknesses or lack of stature would be associated with very poor performance, but once the person moved into the "above normal" field correlations with physiological measures break down. The reason is that there are two quite different ways of scoring points in basketball. Some players score by muscling their way underneath the basket, then jumping up and slamming the ball down into the goal. For players who use this strategy, height and weight are good predictors of success, while hand-eye co-ordination and depth perception are not. The other strategy for scoring is to move quickly backwards, away from your opponent, and toss a high, arcing shot up into the goal, over the heads and hands of the opposition. Players who use this strategy need not be particularly large or strong, but must be quick and have excellent depth perception.

With both the computer and athletic analogies in mind, let us look again at intelligence as defined by psychometric theory. Intelligence tests fall into two broad categories. Tests used for clinical, educational, and industrial prediction are typically (intentionally and properly) designed to be work samples for the endeavors to be predicted. They owe their success to the fact that they test so many behaviors that they are almost bound to produce a good sample of a person's general cognitive capacities (Wechsler, 1975). Given the pragmatic, behavior sampling approach taken in the development of such instruments as the Wechsler and Stanford-Binet tests, it is unreasonable to expect that any one information processing procedure would provide "the answer" to our questions about the nature of intelligence.

A far more interesting group of intelligence tests are those that are derived from an explicit psychometric theory, such as the various tests used to measure "general intelligence" or, even more explicitly, its crystallized and fluid components (Horn, 1979). It is much more reasonable to expect to find that there is a close link between information processing measures and psychometrically pure tests of intellectual functioning than to find such a link between information processing and the behavior-sample type of test. Indeed, such research is currently being conducted in our own laboratory and in others, and we await its outcome with interest.

In spite of the theoretical importance of research linking specific information processing theories to specific psychometric theories. I must admit to having little hope that these studies are going to make a great breach in the .3 barrier. (They may push it back to .4.) The reason for my pessimism is that when psychometric tests are carefully orchestrated so that they are psychometrically pure, they too, bump up against the .3 barrier. This has been illustrated in a convincing way by the research of Snow (in press). By considering the correlation between two tests as an ordinal measure of their similarity, Snow applied multidimensional scaling methods to construct a space of psychometric tests. Figure 5 shows the results. The "good, robust" intelligence tests, i.e. those that are useful in predicting behavior in a variety of situations, all lie in the center of the space. Scattered around the periphery are various tests of specific abilities. These peripheral tests

----

Figure 5 about here

----

are the ones that would be most likely to show high relations to performance in specific information processing paradigms.

I suggest that this picture would be obtained if the peripheral clusters

of tests present people with very restricted problem solving situations, in which there is only one reasonable way to attack the task. Performance in such a situation will be more determined by mechanistic information processing capacities than by strategy choice, simply because of the limited range of strategies possible. By contrast, performance in the central cluster of tests may be much more dependent on a person's having available a store of strategies to deal with the varied problems presented by the items within each test. In this respect, it is of interest to note that the Raven Matrix test (Raven, 1965) appears in the central cluster. Logical analysis of this test has shown that it is amenable to attack by at least two psychologically distinct strategies, one based on perceptual reasoning and one based on propositional reasoning (Hunt, 1976). Statistical analyses of very large samples of persons taking the Raven test have also shown that there are clusters of performance that are, presumably, associated with different strategies. The assumption that the test is some sort of yardstick for a univariate, normally distributed ability cannot explain the pattern of clusters obtained (Hunt, 1978b).

The conclusion that the tests in Snow's central cluster are characterized by their having a number of different solutions, depending on the program the person chooses to use, is reinforced by studies of the individual items in tests that are considered "good indicators of intelligence." Carroll (1976) performed a "Gedanken" experiment, somewhat similar to the analysis of the Raven Matrices, in which he analyzed the information processing requirements of various test items in the Educational Testing Service's reference battery Harman, Ekstrom, & French, 1976. The more complex subtests appeared to Carroll to require more different information processing steps. Still more direct evi-

dence has been obtained by R. Sternberg's (1977, 1977) careful analysis of the time spent in each information processing step during the solution of individual intelligence test items. Consider, for example, the frequently used "analogy problem" item. An example is

DOG is to CAT as WOLF is to (HYENA, LION, SKUNK, FOX).

Sternberg has shown that the solution of such problems can be broken down into several steps; encoding the information associated with each term, comparing the first two terms (DOG, CAT) to each other, inducing the relationship from this comparison, and applying the relationship to map from the third term (WOLF) into one of the possible response terms (HYENA, LION, SKUNK, FOX). Each of these steps calls upon different mechanistic information processing actions. Each step will introduce its own variance into performance on the problem as a whole. Sternberg has also shown that the separate steps can be combined in different orders, and that the importance of an isolated step to total problem solving performance cannot be evaluated without knowing what the combination rule is. If this is true of individual test items, how can we expect to establish correlations between very specific aspects of information processing and total test performance unless we can identify strategies and the people using them?

Strategies as Mediators of Structure: An Illustration

The observation that strategies must be considered in evaluating individual differences in cognitive performance is hardly original. Newell and Simon, surely the leading proponents of the view that thinking can be modeled by computer simulations, have warned that

"A few, and only a few, gross characteristics of the human information

processing system are invariant over tasks and problem solvers."

Newell and Simon, 1972, p. 788.

This is undoubtedly correct. Summarizing the relationship between cognitive performance on two different tasks by a linear equation may give us a picture of population performance that fails to capture the essence of individual problem solving. But what is the alternative to the correlation coefficient? Presenting simulation programs for each person and each task is clearly an inadequate summarization. Having provided an excellent argument for rejecting correlational studies of thinking, the computer simulation approach as yet has not developed an alternative method of stating results. How are we to summarize if each person is unique?

One approach that we can take is to identify groups of people who use similar strategies, and apply correlational analysis within each group. Problem solving strategies can be grouped into large classes, based upon the problem representation that each strategy uses. Psychologists, computer scientists, and educators have long argued that the way in which a problem solver initially represents the problem is one of, if not the, major determinants of performance (Bloom and Broder, 1950; Polya, 1954, 1957; Simon and Hayes, 1976). We can divide representations themselves into two broad classes; linguistic representations or spatial-imaginal representations. The sorts of skills that a problem solver uses to solve a particular problem will depend very much upon which of these two classes of representations are chosen. Furthermore, the argument does not apply only to the very complex problems studied in mathematics or education, we have found that it applies to ostensibly very simple cognitive tasks. When allowance is made for the type of problem representation chosen, and the concomitant choice of strategy, we find

that some puzzling observations about the relationship between information processing and psychometric performance become quite regular.

The task that we have chosen to study is the sentence verification paradigm (Clark and Chase, 1972), a miniature linguistic situation in which verbal statements must be co-ordinated with non-verbal stimuli. In a sentence verification paradigm the participant first sees a sentence describing a simple picture, and then sees the picture. The task is to determine whether or not the sentence accurately describes the picture. Some examples are shown

----
Figure 6 about here
----

in Figure 6. A logical analysis of each sentence is also shown in the figure. This demonstrates that the sentences vary in the extent to which they contain embedded propositions. A number of experiments have shown that the time required to verify a sentence as a description of a picture depends upon the extent of the propositional embedding. (For a review of this literature, see Carpenter and Just, 1975). Furthermore, speed of sentence verification has been shown to correlate moderately well with measures of general verbal comprehension (Baddeley, 1968; Lansman, 1978). On its face, and from a theoretical analysis of the task as an exercise in psycholinguistics, the task appears to be a reliable, rapid way to measure one's competence in dealing with linguistic materials. This is particularly interesting because the test itself is virtually knowledge free, while many conventional tests of language comprehension have been criticized for their dependence upon specific semantic knowledge.

One of the major strengths of the sentence verification task as a measure of language performance is its close tie to theories of psycholinguistic

information processing. As noted, a psycholinguistic approach assumes that sentence verification requires the resolution of various embeddings. The basic ideas of the psycholinguistic approach are that

(a) the picture is represented by the simplest possible propositional representation. Thus the picture ($\overset{*}{+}$) would be represented as STAR ABOVE PLUS.

(b) The process of verification involves successive transformations of the sentence representation until it either matches the picture representation or no further transformations are possible. Thus to resolve STAR NOT BELOW PLUS the marked form BELOW must be converted to NOT ABOVE and the negations must be resolved.

All psycholinguistic information processing models assume that each transformation takes time. They differ only in the way they regard the transformations. Clark and Chase (and Trabasso, Rollins, and Shaugnessey, 1972, in a related paper) estimate parameters for resolving marking, negation, and the affirmative-negative decision separately, whereas Carpenter and Just regard each of these as the same process, requiring estimation of a single parameter. Both models can be shown to account for better than 90% of the variance in the times required to verify different types of sentences. In general, negatively worded sentences require more time to verify, sentences with marked forms take longer to verify, and negative decisions are slower than affirmative decisions. There are also interactions between these effects, which are predicted by the psycholinguistic model. By any account, the fit of the data to the models is impressive.

Most studies of sentence verification have used relatively few subjects, and hence have not studied individual differences. In the course of our

explorations of this task as a measure of linguistic competence, however, we acquired data from some seventy subjects. Averaged over subjects, the data showed a close fit to the expectations of the psycholinguistic models, as is shown in Figure 7. John Palmer and Marcy Lansman realized that the individual

---

Figure 7 about here

---

difference data could be used to discriminate between the two main psycholinguistic models. The "one parameter" model requires that there be a very high correlation between estimates of individual times required to resolve different types of embedding, since each resolution is assumed to be accomplished by the same process. The results are shown in Table 3. The expected high correlations did not appear, so the single parameter model can clearly be rejected. But the multiple parameter model is also in trouble. The reason for this has to do with our estimate of falsification. Two estimates are possible, one for affirmatively worded and one for negatively worded sentences. The two estimates of the same parameter are not correlated. Clearly the models that do so well in handling response times averaged over individuals are doing very poorly when applied to individual differences data.

Table 3 about here

These paradoxical observations have been resolved by a series of experiments conducted by Colin MacLeod, Nancy Mathews, and myself (MacLeod, Hunt, and Mathews, 1978; Mathews, Hunt, and MacLeod, Note 2). To foreshadow, we have shown that the type of information processing underlying sentence verification depends upon how the subject approaches the task. Our procedure, which differs slightly from that used in some other studies, is shown in

Figure 8. The sentence is presented, and left on display until the subject

Figure 8 about here

indicates that it has been comprehended. The time required for this will be called <u>comprehension time</u>. The picture is then presented, and the subject decides whether or not the picture was correctly described by the sentence. The time required for this decision will be called <u>verification time</u>. It is important to remember that verification time is the dependent variable that has been used in other sentence verification tasks.

In our first experiment (MacLeod et al., 1978), we applied Carpenter and Just's one parameter model to both group and individual data. Averaged over subjects, the differences in verification times for the various sentence-picture combinations agreed well with the predictions of the one-parameter model. On an individual basis, however, the fit ranged from very good to very poor. (The same thing was true for Palmer and Lansman's data.) We identified three groups of subjects, subjects whose data conformed closely to the model, subjects whose data appeared to bear no resemblance whatsoever to any data predicted by a psycholinguistic model, and a group of "in between" persons. The first two groups will be referred to as the "well fit" and "poorly fit" groups. As is the historic fate of compromisers, the third group will not be further discussed.

Figure 9 shows the relationship between the predictions of Carpenter and Just's model and the data from the well-fit and poorly-fit groups. The discrepancy is striking. But why? We hypothesized that the two groups were

Figure 9 about here

Figure 10 about here

using qualitatively different strategies. The strategies we believed to be involved are depicted in Figure 10. In the linguistic strategy the subject reads the sentence, remembers it in some form tied to the propositional structure of the sentence, then observes the picture, derives a sentence (or propositional structure) from this observation, and compares the two representations. In the spatial-imaginal strategy the subject reads the sentence, forms a mental image of the picture that is expected, then observes the picture and compares the internal visual representations of the observed and expected display.

Two independent analyses were conducted to test this hypothesis. The linguistic strategy places the burden of translation from one representation to another on the verification stage, while the spatial-imaginal strategy places the burden on the comprehension stage. Accordingly, users of the linguistic strategy should spend more time in verification and less in comprehension, while the reverse should be true of the users of the spatial-imaginal strategy. Table 4 shows the relevant data. This prediction was confirmed. The second analysis, which was especially relevant to individual differences, examined the relationship between verification time and psychometric scores of verbal and spatial aptitude within groups of strategy users. There should be an interaction between predictability and strategy use. Verbal comprehension scores should be closely related to verification for linguistic strategy users, while spatial aptitude scores should be closely related to verification for spatial-imaginal strategy users. The appropriate correlations are shown in Table 5, and are as predicted.

Table 4 about here

Table 5 about here

While the MacLeod et al. study produced a consistent pattern of results, a post hoc analysis of data is always suspect. The Mathews et al. study extended our reasoning by reproducing the data for the two strategies experimentally. The experiment consisted of three sessions, on successive days. On the first day the MacLeod et al. sentence verification procedure was replicated. This will be called the "free" condition. The criteria developed from the MacLeod et al. experiment were used to divide the new sample of subjects into groups, and the anlaysis from the first study was repeated. The same phenomena were observed, as is shown in Figure 11. The second and third days were replications except that the subjects were instructed

----

Figure 11 about here

----

to use one strategy or the other. (As there was no evidence of an effect of order of instructions, this variable will be disregarded.) Figure 12 shows the results. It is clear that our university student subjects were able to perform either in accord with the spatial or linguistic strategies. Thus the MacLeod et al. results should not be interpreted as establishing a type of reasoning, in the sense that such typologies as introvert-extrovert or field dependent-field independent have been proposed. Rather, our results show that above average young adults can shift from one strategy to another relatively easily, and that the underlying abilities that they use to solve an ostensibly linguistic task depend upon strategy choice.

Figure 12 about here

Whether or not less talented subjects could display the same flexibility

in strategy choice is an open question. We need further studies to determine the conditions under which particular types of individuals will use particular strategies. The general point remains valid. The relationship between task performance and information processing capabilities depends upon the individual's choice of how the task is to be done. Most complex problems, including those problems that are typical of general intelligence test items permit considerable flexibility in making this choice.

The Problem of General Intelligence

By stressing the importance of strategy choice in intellectual performance, we implicitly develop an argument for a view of intelligence as a combination of special abilities; i.e. the "ability" to make good strategy choices. The extreme statement of this view is that there is no such thing as general intellectual capacity. Cognitive behavior is instead seen as a compendium of structural capacities and strategies to hold them together. This viewpoint is consistent with much of the thinking in both experimental and psychometric psychology. The quotation from Newell and Simon (see above) is a good summary of its logic. Psychometricians will recognize the specialized viewpoint as being a restatement of Guilford's (1967) view that there are a variety of highly specialized abilities, each defined by stating the type of stimulus material being processes, the type of operation required on it, and the type of answer required. Indeed, Guilford has used this cross-classification scheme to generate a table of over 100 hypothetical abilities!

An opposing view, which dates back to Spearman (1927), and is represented today by Horn (1979) and Jensen (1979) is that there are one or two broadly relevant "general intelligence" capabilities, which permeate virtually all intellectual endeavors. The principal evidence for the general intelligence

viewpoint is the observation that superficially disparate intellectual tasks are almost always positively correlated.

The argument between the generalist and the specialist view does, at times, take some of the aspects of an argument over whether a glass is half full or half empty. The generalist points to the undeniable fact that many cognitive tasks are positively correlated, with r's in the .3 to .4 range. The specialist observes that the r^2 values are only .1 to .2! Granted that this is true, the phenomena of widespread positive correlations between different tests (technically, the phenomenon of positive manifold) is too robust a fact to be ignored. Explaining it within an information processing concept requires that we locate some information processing concept that applies to an equally wide range of behaviors and show that this concept is related to test performance.

There is such a concept, but it does not fit easily into the computer analogy. This is the concept of attentional resources. Probably the most comprehensive recent statement of this concept has been given by Kahneman (1973), although a number of other names are also associated with the idea. (Posner (1978) has cited references to the concept in the late 19th Century and, interestingly, Spearman (1927) made it a prominent part of his theory of general intelligence.)

The basic assumption of "attention theory", for want of a better name, is that every human information processing task requires the allocation of some (rather poorly defined) "attentional resources" for its execution. If less than enough resources have been supplied to a particular mechanistic process, then that process may be able to function but it will do so at a

reduced level of efficiency. Whether or not this will have a catastrophic effect upon thinking depends upon the extent to which the affected process is central in the problem solving strategy being executed. The attentional resource concept is even broader than the concept of general intelligence, for attentional resource demands are assumed to be made by non-intellectual information processing tasks, such as signal detection, as well as by such things as paragraph comprehension and arithmetic problem solving.

Marcy Lansman and I have been exploring the possibility that differential demands for attentional resources can be used to explain individual differences in a wide range of tasks, all of which involve information processing, but not all of which would conventionally be called "thinking". In order to study attention resource demands we have used the "dual task" methodology, in which a person is asked to do two information processing tasks at once. We examine inter-task interference as an indication that the two tasks draw on a common mental resource. Such paradigms have been subjected to extensive theoretical analysis (Posner, 1978; Kerr, 1973; Norman and Bobrow, 1975). Customarily one of the tasks is designated to be the primary task, and the other the secondary task. (For brevity, we shall refer to tasks A and B.) An assumption of the strict secondary task interpretation is that task B is done with whatever spare capacity remains after task A has been executed. This implies that task B should not interfere with task A. We, and others, have found that this assumption can seldom be justified, so we offer a slightly different analysis of the dual task paradigm that does not depend on the primary task-secondary task distinction.

Tasks A and B must be chosen so that it is not reasonable to expect them

compete for the same information processing structures ("structural interference"). For instance, one would certainly not use tasks that required incompatible responses, such as moving a lever in task A and and pressing a button with the same hand in task B. Such gross examples are easy to deal with. In practice,though, the situation may be much more subtle, and whether or not structural interference has been avoided is often a matter of judgement. When it can be, we are justified in saying that any interference between the two tasks must be due to competition for attentional resources. The resource competition itself can be illustrated by an unusually simple "electrical", rather than electronic, analogy. Figure 13 shows a schematic of two machines, one for task A and one for task B, that are attached to the same power source. They compete for resources in the same

---
Figure 13 about here
---

sense that an electric light and an electric washing machine compete for resources in residential electric systems.

In fact, the washing machine analogy can be used to show how the dual task technique can be applied to the study of individual differences. Suppose that Figure 13 was a diagram of a washing machine - light circuit, and that the washing machine was inefficient, and thus exerted a heavy load on the system just before it broke down. In a very simple circuit (i.e. one without safety fuses) the first indication that you would have of a malfunction of the washing machine would be a dimming of the lights, as the appliance began to make excessive demands on the circuit. Lansman and I have used a similar logic in our studies. We have sought tasks A and B that have the following characteristics:

(a) The tasks are sufficiently different so that structural interference is unlikely.

(b) The difficulty, and, in theory, the demand for attentional resources, of task A can be varied in a continuous manner.

(c) The level of performance of task B varies in response to the attentional resources supplied to it.

One series of experiments (Lansman, 1978; Hunt, Lansman, and Wright, Note 4) applied the paradigm to study attentional demands in easy and hard memory tasks. Task A was the continuous paired-associates task developed by Atkinson and Shiffrin (1968). In this task the subject must keep track of the continuously changing state of several variables. This is done by pairing numbers with letters, aperiodically requiring the subject to report the number currently paired with a letter, and then changing the letter-number pairing. The exact procedure is shown in Figure 14. The task can be made arbitrarily difficult by varying the number of letter-number pairs that must be kept in mind. Task B was a simple probe reaction task that was inserted during the memory task. Figure 14 shows the procedure for a visual probe; auditory probes were also used.

Figure 14 about here

Our interest centers on probe performance under memory load conditions (keeping track of two variables) as a predictor of individual performance under <u>hard</u> memory load (seven variables). Recalling the washing machine analogy, probe reaction time under the easy memory condition is analogous to the light's intensity when the washing machine has a small load, and should thus predict, across individuals, those persons who would have the most difficulty in the

memory load were to be increased. The relevant correlations are shown in Table 6. There was a reliable, moderately high correlation between probe reaction time in the easy memory condition and memory performance in

----

Table 6 about here

----

the hard memory condition.

One can object that while this does show that probe reaction and memory do draw upon a common attentional resource, after all, short term memory is not the same as thinking. We have applied the same design to an analysis of two tasks that differed even more radically in their surface characteristics (Hunt et al, Note 4). In this experiment task A was a subset of 18 of the 36 Raven Progressive Matrix problems (Raven, 1965). Raven problems require that the subject detect a relationship between the elements of complex visual pattern, and then apply that relationship to complete a missing part of the pattern. Two samples are shown in Figure 15. As can be seen, the problems vary widely in difficulty. The Raven Matrix problems are particularly

----

Figure 15 about here

----

interesting as a sample Task A because this test is frequently cited as one of the best measures of the general intelligence factor (Jensen, 1979).[4]

Task B was a psychomotor task designed so that it would not normally be considered a test of intelligence. The task, which we call a "Gizmo", requires that the subject hold a lever between two posts, using the thumb and index finger of the left hand. By itself, this is quite easy to do. The task becomes difficult when the subject is distracted, in this case by attempting to solve Raven Matrix problems that were projected onto a screen immediately in front of the subject. Procedurally, the subject first

practiced with the Gizmo alone, then solved 18 Raven problems alone, and then solved 18 Raven problems while trying to hold the Gizmo in place. The Raven problems were presented in ascending order of difficulty, as defined by the extensive norms available for the test (Forbes, 1964.)

If both the Raven Matrices and the Gizmo are drawing on the same attentional resources, then performance on the Gizmo task should deteriorate as Raven problems become harder, as, indeed, it does. It is difficult to interpret this, however, as we do not have a clear model for attention allocations as the subject begins to "break down", by making errors on more difficult problems. A more sensitive test is to observe Gizmo performance before the subject makes an error on the Raven items. As a person approaches the first Raven problem that represents, for that individual, a non-trivial problem, the person's Gizmo performance should deteriorate. Just where this happens in the sequence of Raven items, however, will vary from individual to individual.

There are two ways that this prediction can be tested. By the same logic that applied in the memory experiment, there should be a correlation between individual psychomotor performance on the first five problems (on which virtually no errors are made) and the point at which a person makes his or her first error. The correlation was -.30, which was statistically significant at the .02 level. Note that this cannot be explained by assuming differential concentration on one task or the other, because people who are doing well on the psychomotor task also do well on the Raven problems. Also, the correlation was calculated after partialling performance on the psychomotor task alone,

and hence cannot be explained by assuming that people who do well on the psychomotor task also do well on the intelligence test.

The effect can be shown somewhat more graphically by plotting psychomotor performance on the three problems just prior to problem N, as a function of N. Figure 16 shows this for two groups of subjects; those who make their first error on problem N and those who make their first error on some problem

----
Figure 16 about here
----

beyond problem N. Clearly the subjects who are about to make an error show worse performance on the psychomotor task while solving problems just prior to their first error.

The data from both the memory and the Raven tasks are clearly compatible with the assumption that intellectual and psychomotor information processing tasks draw on a common source of attentional resources. This, of course, does not mean that there is a single pool of such resources. There may very well be several, and "intellectual" tasks may draw on only some of them. Further, the very simple model in which the tasks compete equally for resources is unlikely to be correct. We need to investigate more closely different models for allocation of resources during reasoning. In spite of these reservations, Spearman's notion of "mental energy" seems to be a surprisingly good first approximation for explaining the general intelligence phenomenon.

Concluding Comments

People differ widely in how, and how well, they think. One of the biggest sources of individual variance in thought is simply knowledge, different people know different things. Psychological research on intelligence has tended to disregard this, regarding it more properly as part of the realm of education or

sociology. The role of knowledge must be included in any comprehensive account of individual cognition. On the other hand, there are situations in which wide ranges of cognitive ability are displayed when it seems unlikely that knowledge is a determinant of differential performance. The experiments reported here are examples.

Three sources of individual differences in information processing have been proposed; structure, process, and attentional resource allocation. These factors should affect cognitive competence in different ways. Structural resources set limits on the effectiveness of specific information processing steps. Such processes appear to be important when we contrast the cognitive capacities of quite different individuals, such as the contrast between normally and mentally retarded persons. As we learn more about subpopulations within such extreme groups we may very well find that there are specific structural changes that apply to each normal-"unusual group" contrast. For example, there is already evidence that specific types of mental retardation will lead to specific information processing deficits (Money, 1964; Warren, 1978).

Attentional and process differences exert powerful but more transient effects on cognition. Not only do we think differently between ourselves, each of us varies in our own thought processes from time to time. Structural influences on thought will be mediated by strategy choice, so which of our basic capacities influences our thinking may often depend on how we are thinking at the time. While there is undoubtedly some truth in the notion of general cognitive styles, it would be a mistake to think that a given individual has a fixed style of thought. More studies are needed of the interaction between personal and situational characteristics and an individual's choice of

problem representation and problem solving strategy. Our results indicate that these variables can operate in what would appear to be, superficially, very simple problem solving situations. More complex situations than sentence verification undoubtedly offer an opportunity for a much greater choice of strategy!

It has been argued that the phenomenon of positive manifold, the tendency for intellectual tasks to be positively correlated (in spite of the effect of strategy choice just described), can be derived from the concept of attentional resources, applied to complex problem solving situations. For the same reason, we expect correlations between intellectual performance and perceptual-psychomotor performance under stressful conditions. We also expect to find mutual interference between intellectual tasks and demanding psychomotor activity. (Indeed, such interference was found in the dual task studies described above.) Airplane pilots should not compose poetry during landings.

Psychologists and sociologists have frequently discussed the causal correlates of cognition. Studies have been performed relating cognitive performance to variables such as education, nutrition, socioeconomic status, genetic constitution, and nutrition. The information processing view of cognition suggests that some thought be given to how these variables are supposed to mediate our ability to think. Variables that represent relatively permanent characteristics of an individual, such as sex, genetics structure, and chronic injury, can presumably affect structure. Attentional resource changes may also be subject to such influences, but they will also reflect transient changes in an individual's physical state, responding to such things as the acute effects of drugs or illness, fatigue, and diurnal variation. Process differences are subject to a still wider range of influences. The problem solving strategies a person

could use will be determined by attentional and structural resources. The strategies that he or she actually will use will, within limits, be determined by education in its broadest sense. How has the person learned to solve problems? Who can learn to apply what strategies? It is my belief that more will be learned about the nature of cognition and its antecedents if we study the role of such causal agents directly upon measures of information processing structure, attention, and strategy choice than will be learned from studies in which the dependent variables are extremely complex "intelligence tests".

Reference Notes

1. Keele, J. Presentation at Office of Naval Research Contractor's Meeting on Information Processing Abilities. New Orleans, Louisiana, February 1979.

2. Parkinson, S. Information processing in the aged. Paper presented at the Sandoz Conference on Aging, Battelle Memorial Institute, Seattle, Washington, 1977. (Available from Stanley Parkinson, Department of Psychology, Arizona State University, Tempe, Arizona 85281.)

3. Mathews, N. N., Hunt, E., & MacLeod, C. Strategy choice and strategy and strategy training in sentence-picture verification. Manuscript submitted for publication, 1979.

4. Hunt, E., Lansman, M., & Wright, J. Some remarks on doing two things at once (Technical Report). Seattle, Wa.: University of Washington, Department of Psychology, April 1979.

References

Atkinson, R. C., & Shiffrin, R. M. Human memory: A proposed system and its control processes. In K. Spence & J. Spence (Eds.), The psychology of learning and motivation. II. New York: Academic Press, 1968.

Baddeley, A. D., & Hitch, G. Working memory. In G. H. Bower (Ed.), The psychology of learning and motivation (Vo.. 8). New York: Academic Press, 1974.

Bloom, B. S., & Broder, L. Problem solving processes of college students: An exploratory investigation. Chicago: University of Chicago Press, 1950.

Carpenter, P. A., & Just, M. A. Sentence comprehension: A psycholinguistic processing model of verification. Psychological Review, 1975, 82, 45-73.

Carroll, J. B. Psychometric tests as cognitive tasks: A new "structure of intellect". In L. Resnick (Ed.) The nature of intelligence. Hillsdale, N.J.: Lawrence Erlbaum Associates, 1976.

Cavanagh, J. P. Relation between the immediate memory span and the memory search rate. Psychological Review, 1972, 3, 472-517.

Chiang, A., & Atkinson, R. C. Individual differences and inter-relationships among a select set of cognitive skills. Memory and Cognition, 1976, 4, 661-672.

Clark, H. H., & Chase, W. G. On the process of comparing sentences against pictures. Cognitive Psychology, 1972, 3, 472-517.

Ellis, N. R. Do the mentally retarded have poor memory? Intelligence, 1978, 2, 41-54.

Forbes, A. R. An item analysis of the advanced matrices. British Journal of Educational Psychology, 1964, 34, 1-14

Goldberg, R. A., Schwartz, S., & Stewart, M. Individual differences in cognitive processes. Journal of Educational Psychology, 1977, 69, 9-14.

Guilford, J. P. The nature of human intelligence. New York: McGraw-Hill, 1967.

Harman, H. H. Ekstrom, R. B., & French, J. W. Kit of factor reference cognitive tests. Princeton, N.J.: Educational Testing Service, 1976.

Harris, G. J. & Fleer, R. E. High speed memory scanning in mental retardates: Evidence for a central processing deficit. Journal of Experimental Child Psychology, 1974, 17, 452-459.

Hogaboam, T. W., & Pellegrino, J. W. Hunting for individual differences in cognitive processes: Verbal ability and semantic processing of pictures and words. Memory and Cognition, 1978, 6, 189-193.

Horn, J. L. Intelligence - Why it grows, why it declines. In L. Willerman & R. G. Turner (Eds.) Readings about individual differences and group differences. San Francisco: W. H. Freeman and Co., 1979.

Hunt, E. Quoth the raven? Nevermore! In L. Gregg (Ed.) Knowledge-Cognition. Hillsdale, N.J.: Lawrence Erlbaum Associates, 1974.

Hunt, E. Mechanics of verbal ability. Psychological Review, 1978 a, 85, 109-130.

Hunt, E. Qualitative sources of individual differences in complex problem solving. In J. M. Scandura & C. J. Brainerd (Eds.), Structural/process models of complex human behavior. The Netherlands: Sijthoff & Noordhoff, 1978 b.

Hunt. E. B., & Love, T. How good can memory be? In A. Melton & E. Martin (Eds.), Coding processes in human memory. V. H. Winston & Sons, 1972.

Hunt, E., Lunneborg, C., & Lewis, J. What does it mean to be high verbal? Cognitive Psychology, 1975, 7 194-227.

Huttenlocher, J. & Burke, D. Why does memory span increase with age? Cognitive Psychology, 1976, 8, 1-31.

Jensen, A. R. g: Outmoded thoery or unconquered frontier? Creative Science & Technology, 1979, 2, 16-29.

Kahneman, D. Attention and effort. Englewood Cliffs, N.J.: Prentice-Hall, 1973.

Keating, D. P. , & Bobbitt, B. L. Individual and developmental differences in cognitive-processing components of mental ability. Child Development, 1978, 49, 155-167.

Kerr, B. Processing demands during mental operations. Memory and Cognition, 1973, 1, 401-412.

Lansman, M. An attentional approach to individual differences in immediate memory (Technical Report). Seattle, Wa.: University of Washington, June 1978.

Lunneborg, C. E. Choice reaction time: What role in ability measurement? Applied Psychological Measurement, 1977, 1, 309-330.

Lyon, D. R. Individual differences in immediate serial recall: A matter of mnemonies? Cognitive Psychology, 1977, 9, 403-411.

MacLeod, C. M., Hunt, E., & Mathews, N. N. Individual differences in the verification of sentence-picture relationships. Journal of Verbal Learning and Verbal Behavior, 1978, 17, 493-507.

Matarazzo, J. D. Wechsler's measurement and appraisal of adult intelligence (2nd ed.). Baltimore: Williams and Wilkins, 1972.

Miller, G. A. The magic number seven, plus or minus two: Some limits on our capacity for processing information. Psychological Review, 1956, 63, 81-97.

Money, J. Cytogenic and psychosexual incongruities with a note on space-form blindness. American Journal of Psychiatry, 1964, 119, 820-827.

Newell, A., & Simon, H. Human problem solving. Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1972.

Norman, D. A., & Bobrow, D. B. On data-limited and resource limited processes. Cognitive Psychology, 1975, 7, 44-64.

Polya, G. Mathematics and plausible reasoning (2 vols.). Princeton, N.J.: Princeton University Press, 1954.

Polya, G. How to solve it. New York: Random House, 1957.

Posner, M. I. Chronometric explorations of mind. Hillsdale, N.J.: Lawrence Erlbaum Associates, 1978.

Posner, M. I., & Mitchell, R. F. Chronometric analysis of classification. Psychological Review, 1967, 74, 392-409.

Raven, J. C. Advanced Progressive Matrices , Sets I and II. London: H. K. Lewis, 1965.

Simon, H. A. & Hayes, J. R. The understanding process: Problem isomorphs. Cognitive Psychology, 1976, 8, 165-190.

Snow, R. E. The interaction of aptitude and performance. In R. E. Snow and P. A. Federico (Eds.) Aptitude, learning, and instruction: Cognitive process analyses. Hillsdale, N.J.: Lawrence Erlbaum Associates, (in press).

Spearman, C. The abilities of man. New York: MacMillan, 1927.

Sternberg, R. Intelligence, information processing, and analogical reasoning. Hillsdale, N.J.: Lawrence Erlbaum Associates, 1977.

Sternberg, R. J. Component processes in analogical reasoning. Psychological Review, 1977, 84, 353-378.

Sternberg, S. High speed scanning in human memory. Science, 1966, 153, 652-654.

Sternberg, S. Memory scanning: New findings and current controversies. Quarterly Journal of Experimental Psychology, 1975, 27, 1-32.

Trabasso, T., Rollins, H., & Shaughnessey, E. Storage and verification stages in processing concepts. Cognitive Psychology, 1971, 2, 239-289.

Underwood, B. J. Individual differences as a crucible in theory construction. American Psychologist, 1975, 30, 128-134.

Underwood, B. J. Boruch, R. F., & Malmi, R. A. Composition of episodic memory. Journal of Experimental Psychology: General, 1978, 107, 393-419.

Warren, J. L. Syndrome differences in the cognitive processing of mildly retarded children and adolescents. Unpublished doctoral dissertation. University of Washington, 1978.

Wechsler, D. Intelligence defined and redefined: A relativistic appraisal. American Psychologist, 1975, 30, 135-139.

Footnotes

The preparation of this paper was supported by the Office of Naval Research, through a contract to the University of Washington (Contract No. N00014-77-C-0225), on which Earl Hunt is the principal investigator. The research reported here was supported by that contract and by a grant from the National Institute of Mental Health, "Individual Differences in Cognition", to the University of Washington (MH-21795). This paper is the text of a talk given at the Annual Conference of the British Psychological Society, April, 1979, at the University of Nottingham, England. I would like to thank Colene McKee for her assistance in preparing this paper.

[1]It is important that some method of controlling for motor reaction time be introduced into experiments of this sort. Most of the variance in reaction times in stimulus identification studies is, in fact, associated with simple choice reaction times, including the time required to move the fingers. Negative results are quite likely in studies that fail to control for this effect (e.g. Hogaboam and Pellegrino, 1978).

[2]In general, correlations between reaction time studies and test scores should be negative, as long RTs reflect poor performance.

[3]This raises the interesting question "What is clinically significant?" Language is a product of the interaction between social and biological evolution, and may very well have developed in such a way that "proper speaking" means that the speaker produces language in such a way as not to overtax the information processing capacities of all but a very few members of the population. Put another way, human language must adjust to the lowest information processing capacity that would be considered "normal", not to the average. If Mnemonists constituted 95 per cent of the population we might have developed

a very different communication system.

[4]Referring back to Figure 5, we see that the Raven test is located near tests that Horn and Cattell categorize as fluid intelligence (Gf) tests. Hunt (1976) has shown that the test can be attacked using a number of different strategies. Interestingly, Spearman (1927) agreed with the conclusion that the test measures g.

GROUP	TEST	r
Warren- Grade School Children	WISC	-.34
Lansman- College Students	WPCT-V	-.29

Table 1. Correlations of stimulus identification (NI-PI) performance with verbal intelligence

FACTOR	1	2	3	4	5	6
	PAIRED ASSOC.	SIMULT. LEARN.	SERIAL LIST	VERBAL DISCRIM.	FREE RECALL	SAT
SAT-V LOADING	.23	.15	-.28	.02	.20	.51
	Communality of SAT-V = .46					

Table 2: Loading of verbal comprehension test on various memory factors

	Fals.I	Fals.II	Below Time rel.=.52
NEGATION TIME (TN+FN)-(TA+FA) rel. = .91	.28**	.32**	.22*
FALSIFICATION I (FA-TA) rel.=.74		.10	.44**
FALSIFICATION II (TN-FN) rel.=.77			.17

Table 3: Correlations between parameters, all subjects.

Group	Comprehension	Verification
WELL FIT ($\underline{n}$ = 43)	1652	1210
POORLY FIT ($\underline{n}$ = 16)	2579	651

Table 4: Mean overall Comprehension RT and Verification RT for Well Fit and Poorly Fit Groups.

Group	Nelson-Denny Comprehension	WPC Verbal	WPC Spatial
WELL FIT	-.47*	-.52*	-.32
POORLY FIT	-.03	-.33	-.68*

Note: Those correlations marked with an asterisk are significant beyond $p < .01$.

Table 5. Correlations of Psychometric scores with Mean Verification RT.

		PROPORTION CORRECT	
		Easy Recall	Hard Recall
	Control Condition	-.09	-.05
PROBE RT	Easy Recall Condition	-.27*	-.40**
	Hard Recall Condition	.01	.07

Table 6: Correlations between Probe RT and Recall Scores

Figure Captions

Figure 1. The stimulus identification paradigm. The first pair exemplifies the physical identity condition (PI), the second pair the name identity (NI) condition, and the third pair the different condition.

Figure 2. Mean difference between name identity and physical identity RTs for groups varying in intellectual ability.

Figure 3. The memory scanning paradigm. In the example at the top of the figure, the subject is first presented with the memory set "1, 3, 5, 7." The probe item "6" is then presented and the subject is to respond as to whether "6" was a member of the memory set. The graph below illustrates the typical finding that RT is a linear function of the size of the memory set.

Figure 4. Functions relating RT to memory set size in the memory scanning paradigm for groups varying in intellectual ability.

Figure 5. Multidimensional scaling of between-test correlations in a battery administered to high school students (N = 241). W identifies subjects of the Wechsler Adult Intelligence Scale. (Taken from Snow, in press.)

Figure 6. Sample sentence verification items.

Figure 7. Comparison of observed group means and values predicted from the Clark and Chase model of the sentence verification task.

Figure 8. The sentence verification paradigm with sequential presentation of sentence and picture.

Figure 9. Mean verification RTs of the well fit and poorly fit groups as a function of the number of constituent comparisons hypothesized by Carpenter and Just's model. Also included are the 95% confidence intervals, and the best fitting straight line for the well fit group only.

Figure 10. Flow chart representations of the strategies believed to be used by the well fit and poorly fit groups.

Figure 11. Mean verification RTs of the well fit and poorly fit groups as a function of the number of constituent comparisons hypothesized by Carpenter and Just's model. Results are for the first day of the study, during which subjects received no instructions concerning strategy.

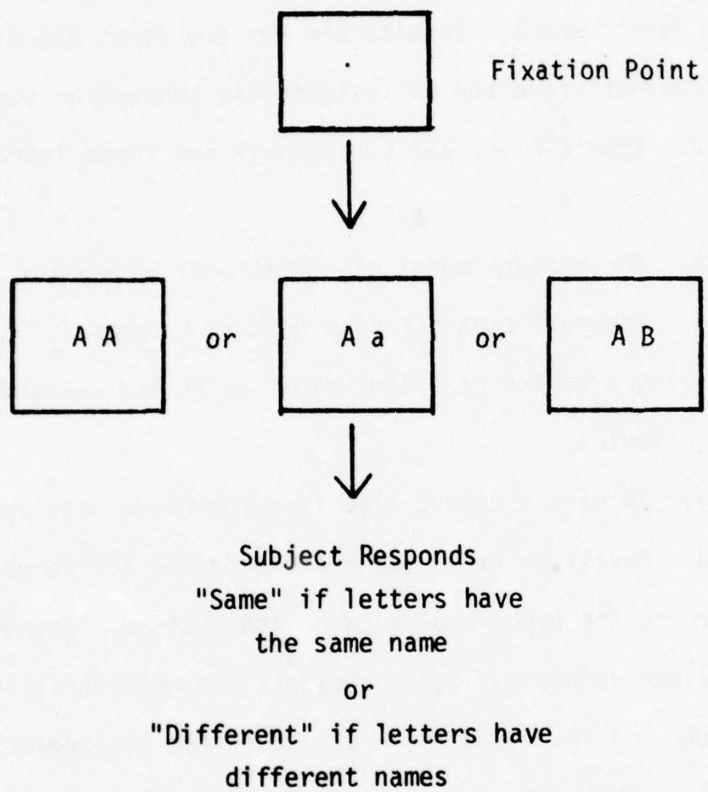
Figure 12. Mean RTs for all subjects in the three instructional conditions.

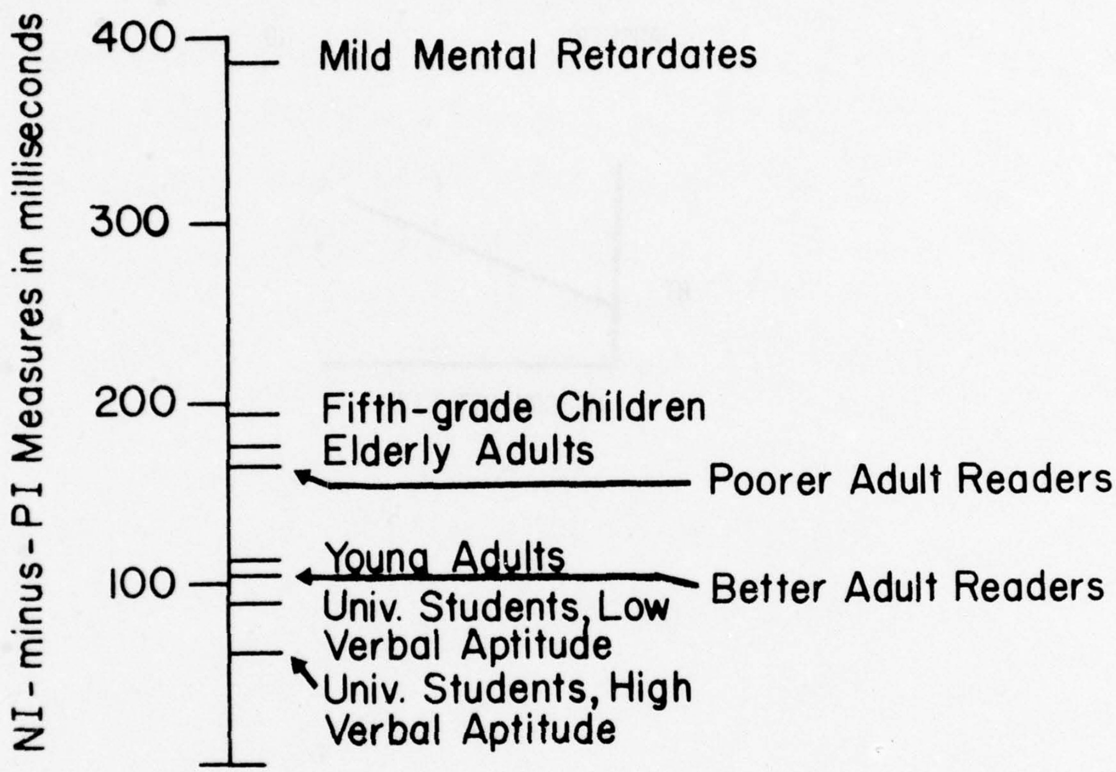
Figure 13. The battery model of attentional resources.

Figure 14. The dual task paradigm used by Lansman (1978), which involved recalling a series of letter-digit pairs and responding to a simple visual stimulus.

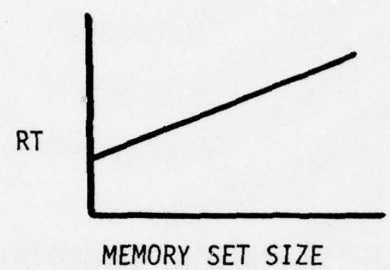
Figure 15. An easy and hard item from the Raven Matrices Test (1965).

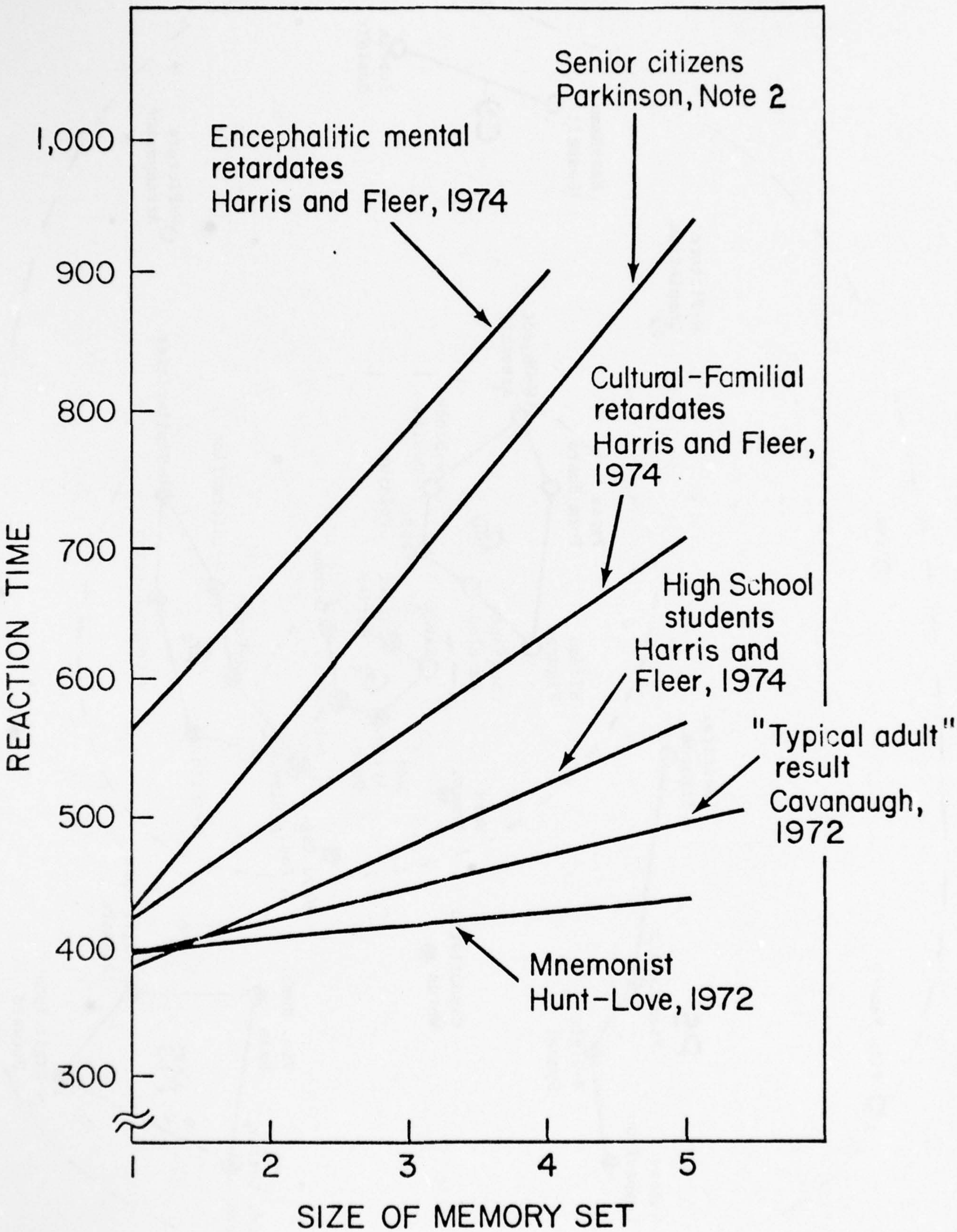
Figure 16. Deviation rate on the Gizmo during the three Raven problems preceding the problem plotted on the abcissa. The dotted line represents the performance of those subjects who made their first error on that problem, and the solid line represents the performance of those subjects who made their first error on a later problem in the sequence.

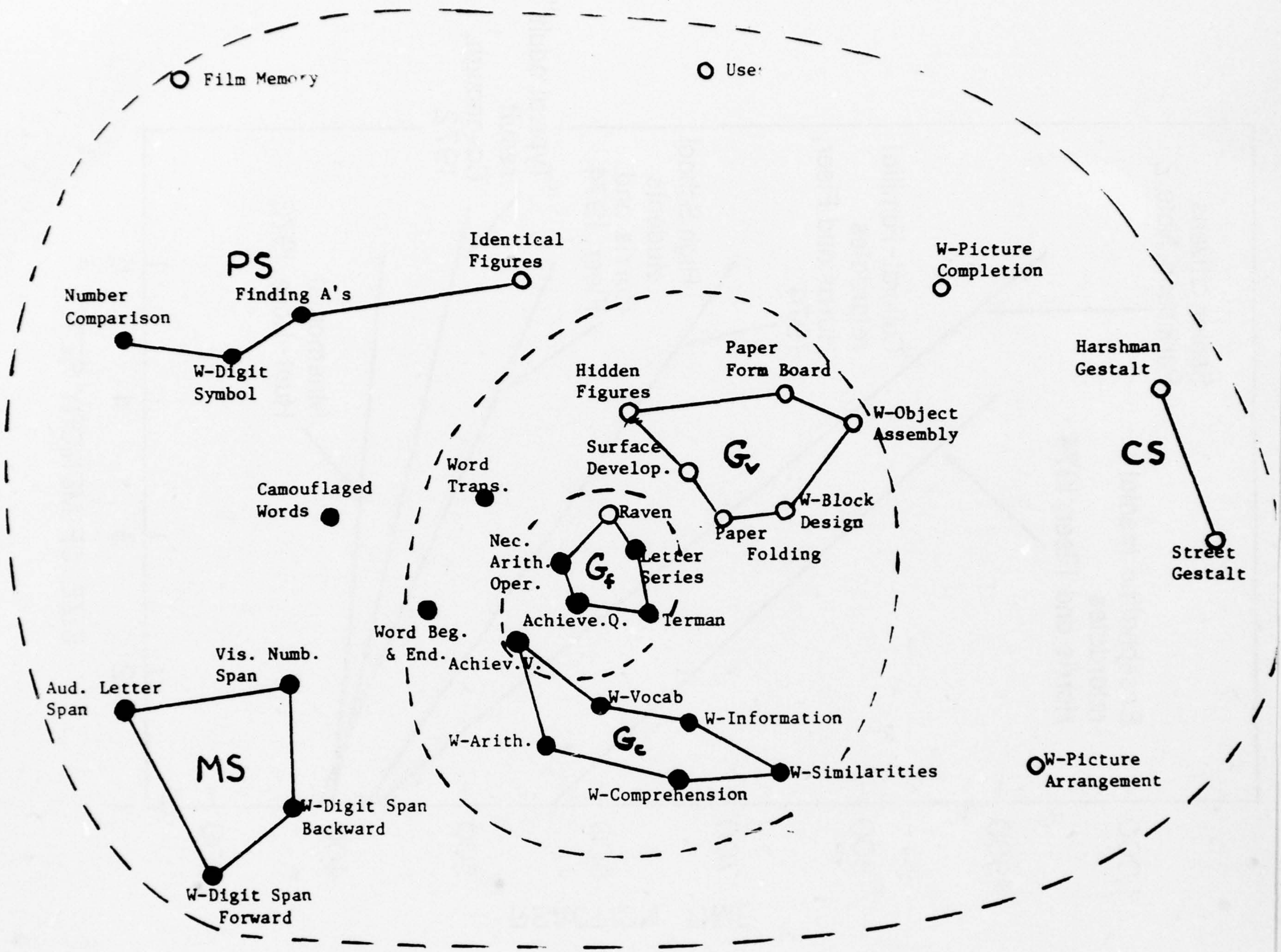

Fixation Point
A A
or
A a
or
A B
Subject Responds
"Same" if letters have
the same name
or
"Different" if letters have
different names


NI-minus-PI Measures in milliseconds
400
300
200
100
Mild Mental Retardates
Fifth-grade Children
Elderly Adults
Poorer Adult Readers
Young Adults
Better Adult Readers
Univ. Students, Low Verbal Aptitude
Univ. Students, High Verbal Aptitude

MEMORY SET	1,3,5,7
PROBE	?6?
ANSWER	NO

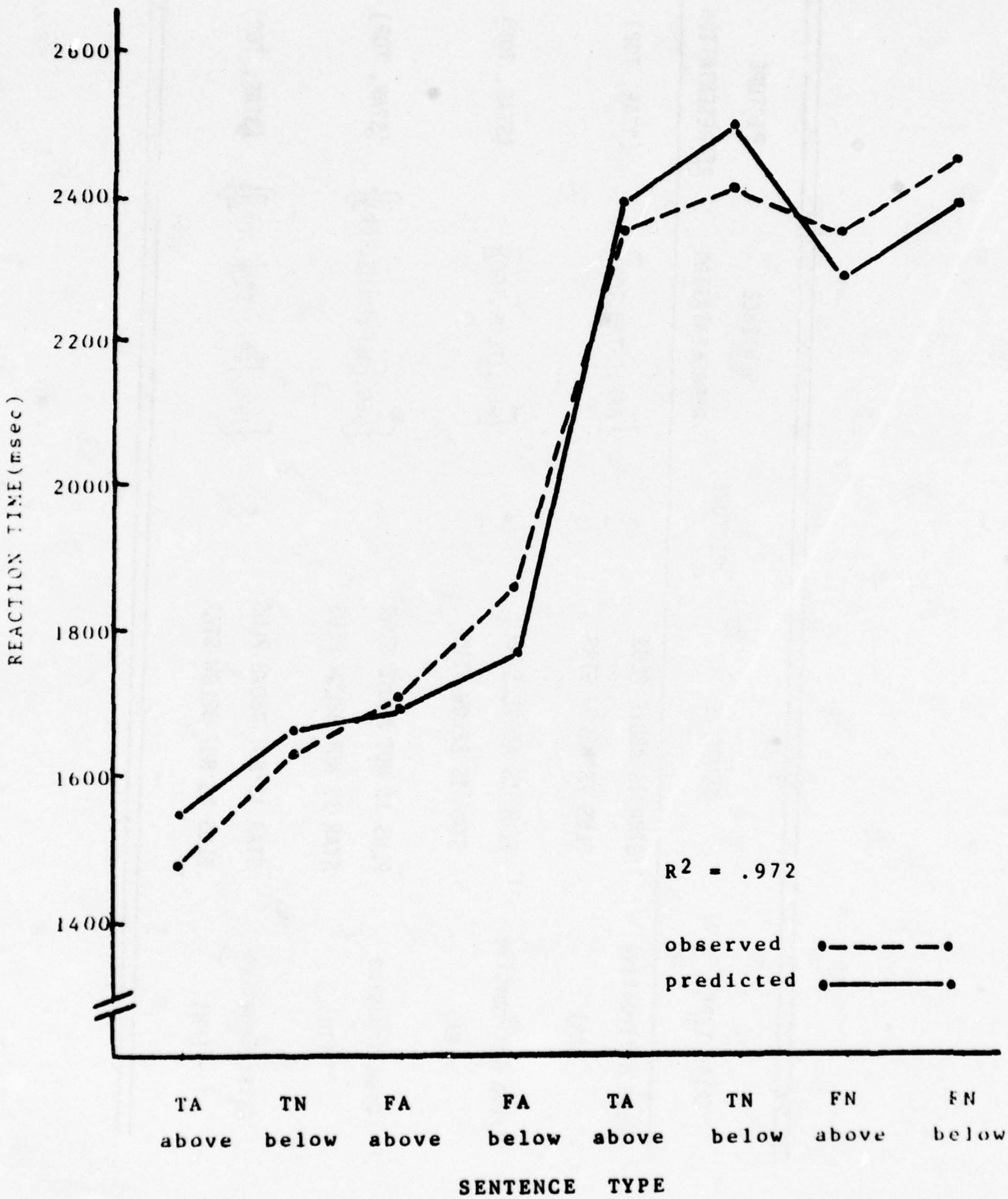



Senior citizens
Parkinson, Note 2
Encephalitic mental
retardates
Harris and Fleer, 1974
Cultural-Familial
retardates
Harris and Fleer,
1974
High School
students
Harris and
Fleer, 1974
"Typical adult"
result
Cavanaugh,
1972
Mnemonist
Hunt-Love, 1972
REACTION TIME
1,000
900
800
700
600
500
400
300
1
2
3
4
5
SIZE OF MEMORY SET

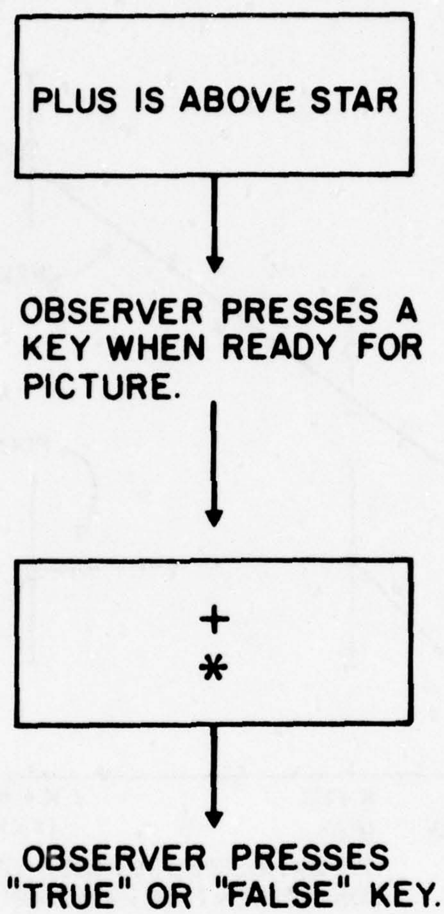


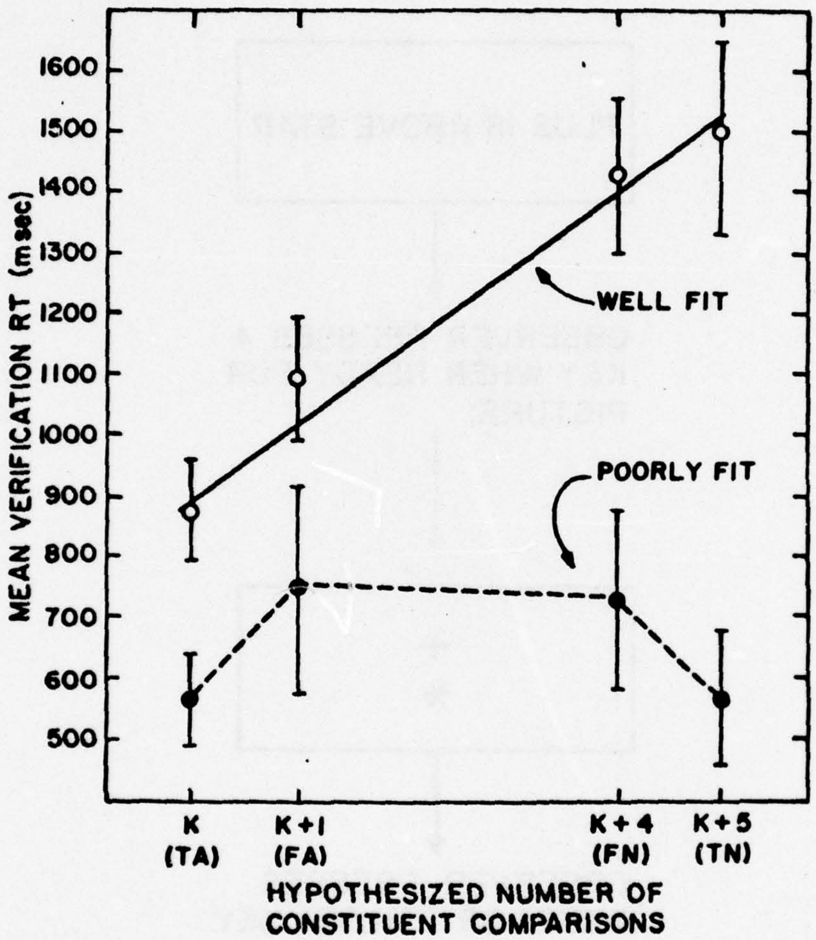
Film Memory
Use
Identical Figures
PS
Number Comparison
Finding A's
W-Digit Symbol
W-Picture Completion
Paper Form Board
Hidden Figures
W-Object Assembly
Harshman Gestalt
CS
Surface Develop.
G_v
Word Trans.
Camouflaged Words
W-Block Design
Raven
Paper Folding
Street Gestalt
Nec. Arith. Oper.
G_f
Letter Series
Achieve.Q.
Terman
Word Beg. & End.
Achiev.V.
Vis. Numb. Span
Aud. Letter Span
W-Vocab
W-Information
W-Arith.
G_c
MS
W-Similarities
W-Picture Arrangement
W-Comprehension
W-Digit Span Backward
W-Digit Span Forward

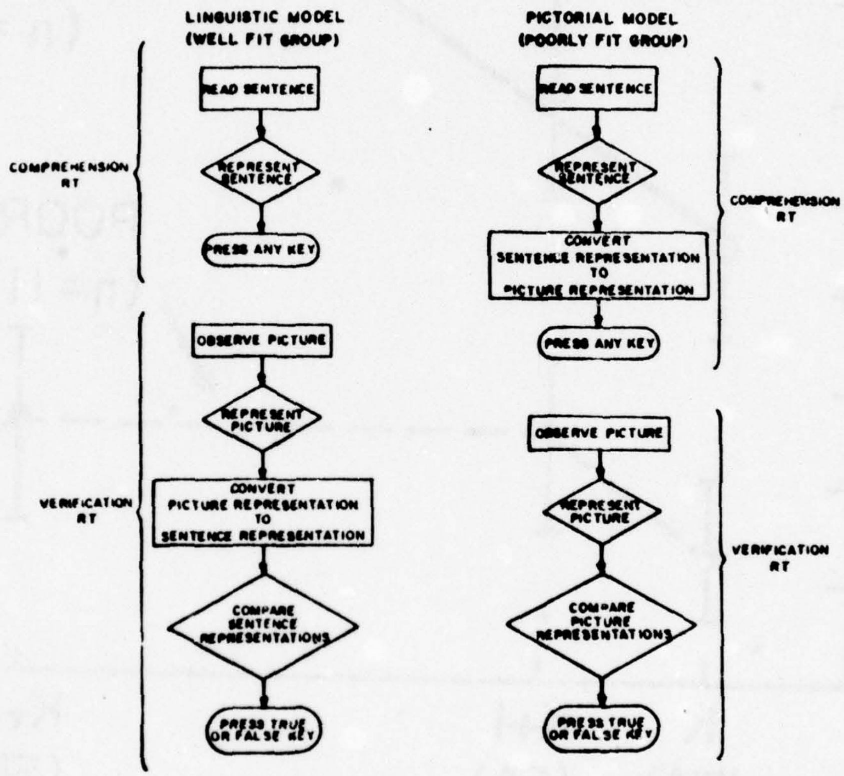
TRIAL TYPE	SENTENCE	PICTURE	SENTENCE REPRESENTATION	PICTURE REPRESENTATION
True Affirmative (TA)	STAR IS ABOVE PLUS PLUS IS BELOW STAR	* +	[AFF,(STAR,TOP)]	(STAR, TOP)
False Affirmative (FA)	PLUS IS ABOVE STAR STAR IS BELOW PLUS	* +	[AFF,(PLUS,TOP)]	(STAR, TOP)
True Negative (TN)	PLUS IS NOT ABOVE STAR STAR IS NOT BELOW PLUS	* +	{NEG,[AFF,(PLUS,TOP)]}	(STAR, TOP)
False Negative (FN)	STAR IS NOT ABOVE PLUS PLUS IS NOT BELOW STAR	* +	{NEG,[AFF,(STAR,TOP)]}	(STAR, TOP)



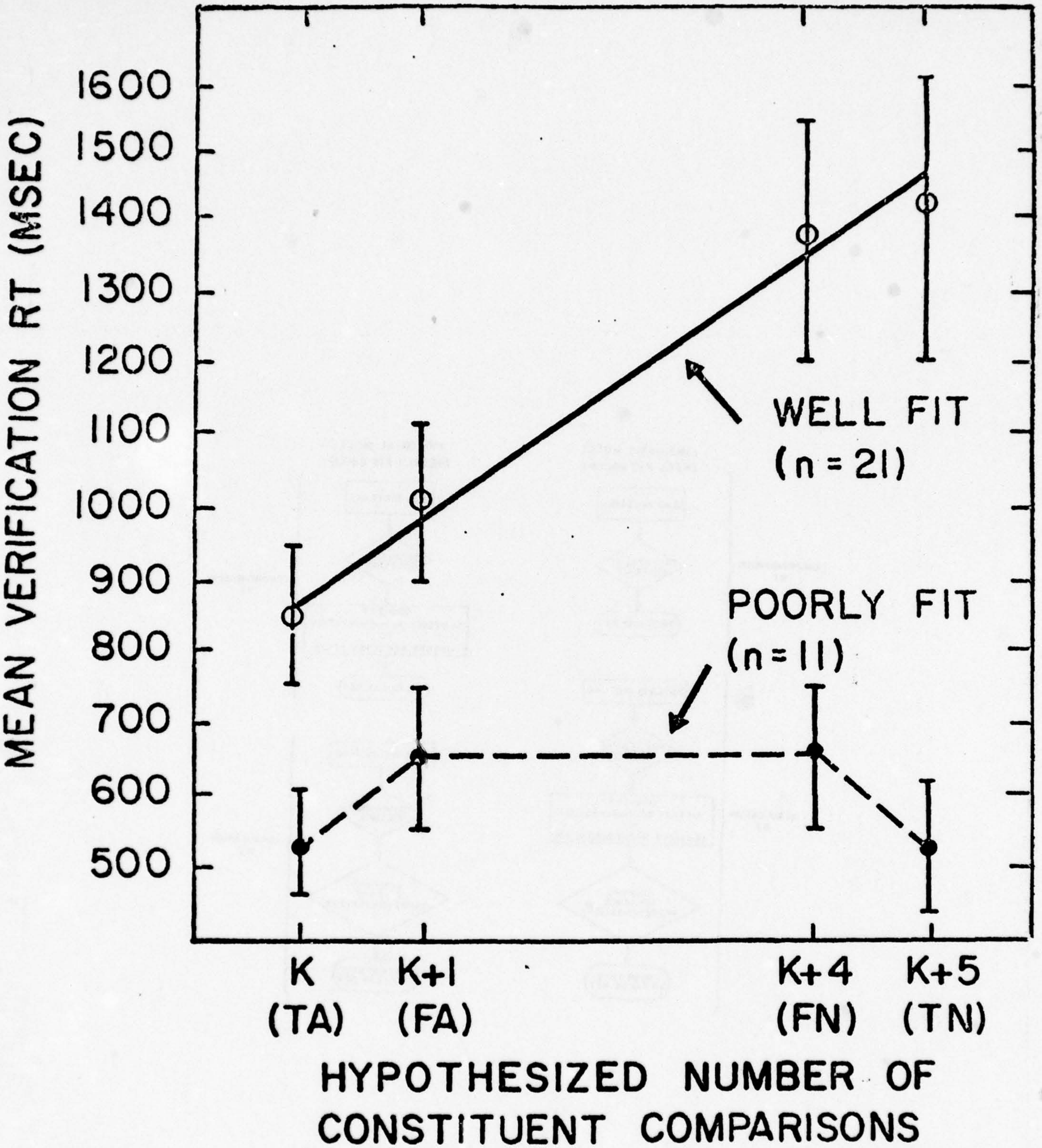
2600
2400
2200
2000
1800
1600
1400
REACTION TIME (msec)
R^2 = .972
observed
predicted
TA above
TN below
FA above
FA below
TA above
TN below
FN above
FN below
SENTENCE TYPE


PLUS IS ABOVE STAR
OBSERVER PRESSES A KEY WHEN READY FOR PICTURE.
+
*
OBSERVER PRESSES "TRUE" OR "FALSE" KEY.

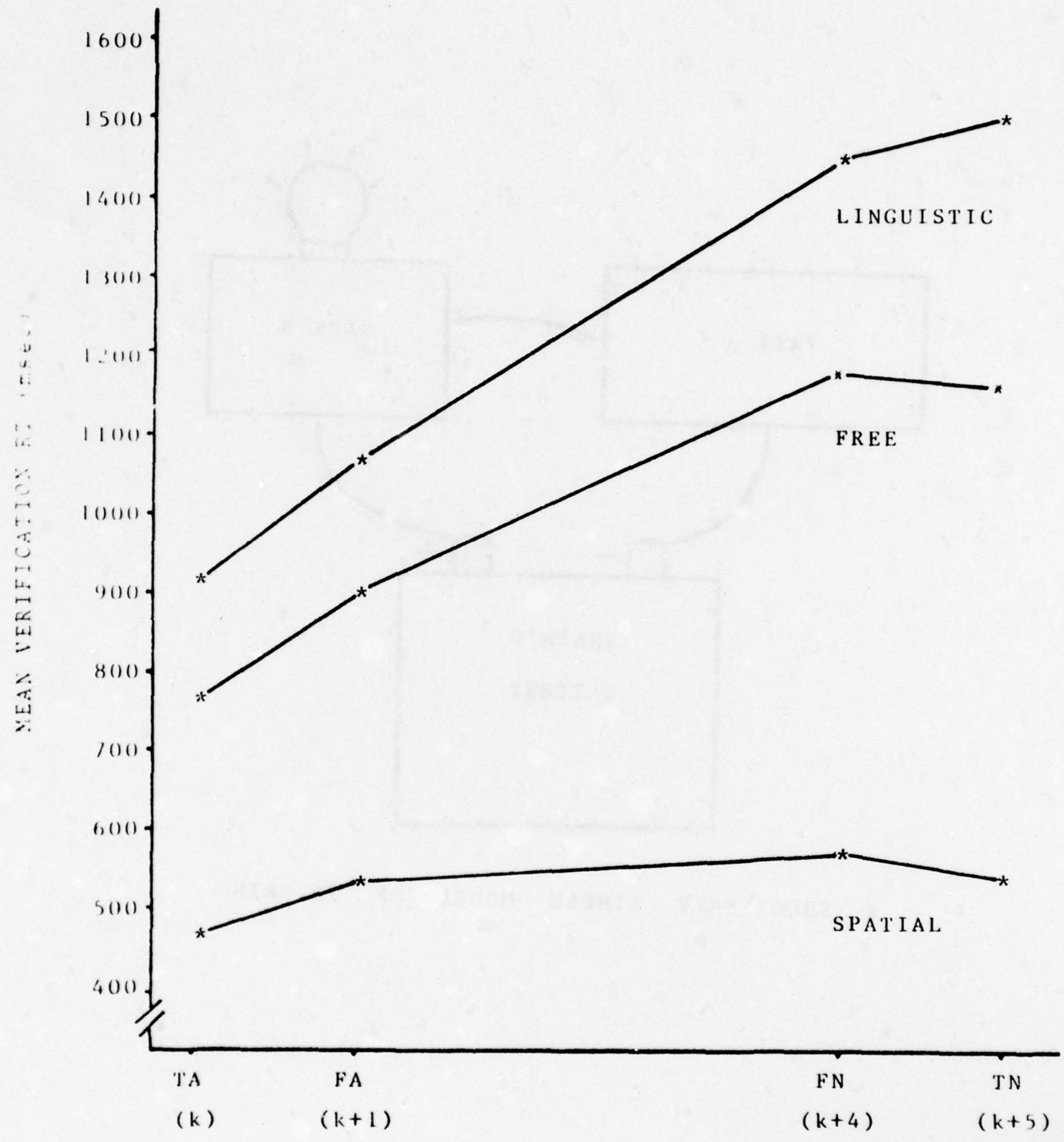

MEAN VERIFICATION RT (msec)
1600
1500
1400
1300
1200
1100
1000
900
800
700
600
500
WELL FIT
POORLY FIT
K
(TA)
K+1
(FA)
K+4
(FN)
K+5
(TN)
HYPOTHESIZED NUMBER OF
CONSTITUENT COMPARISONS

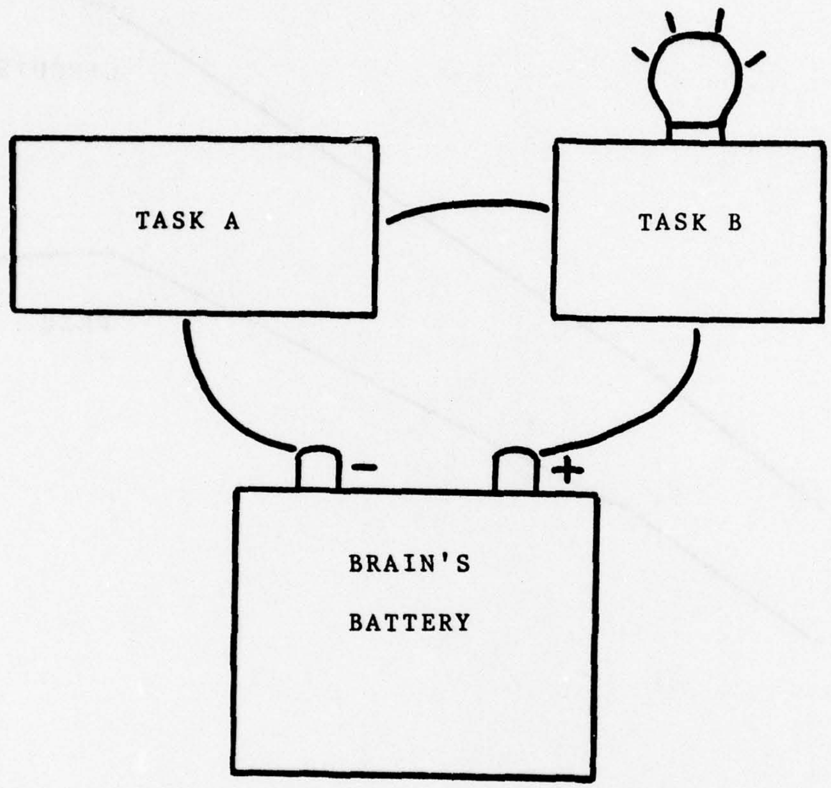


LINGUISTIC MODEL
(WELL FIT GROUP)
READ SENTENCE
REPRESENT SENTENCE
PRESS ANY KEY
COMPREHENSION RT
OBSERVE PICTURE
REPRESENT PICTURE
CONVERT PICTURE REPRESENTATION TO SENTENCE REPRESENTATION
COMPARE SENTENCE REPRESENTATIONS
PRESS TRUE OR FALSE KEY
VERIFICATION RT
PICTORIAL MODEL
(POORLY FIT GROUP)
READ SENTENCE
REPRESENT SENTENCE
CONVERT SENTENCE REPRESENTATION TO PICTURE REPRESENTATION
PRESS ANY KEY
COMPREHENSION RT
OBSERVE PICTURE
REPRESENT PICTURE
COMPARE PICTURE REPRESENTATIONS
PRESS TRUE OR FALSE KEY
VERIFICATION RT



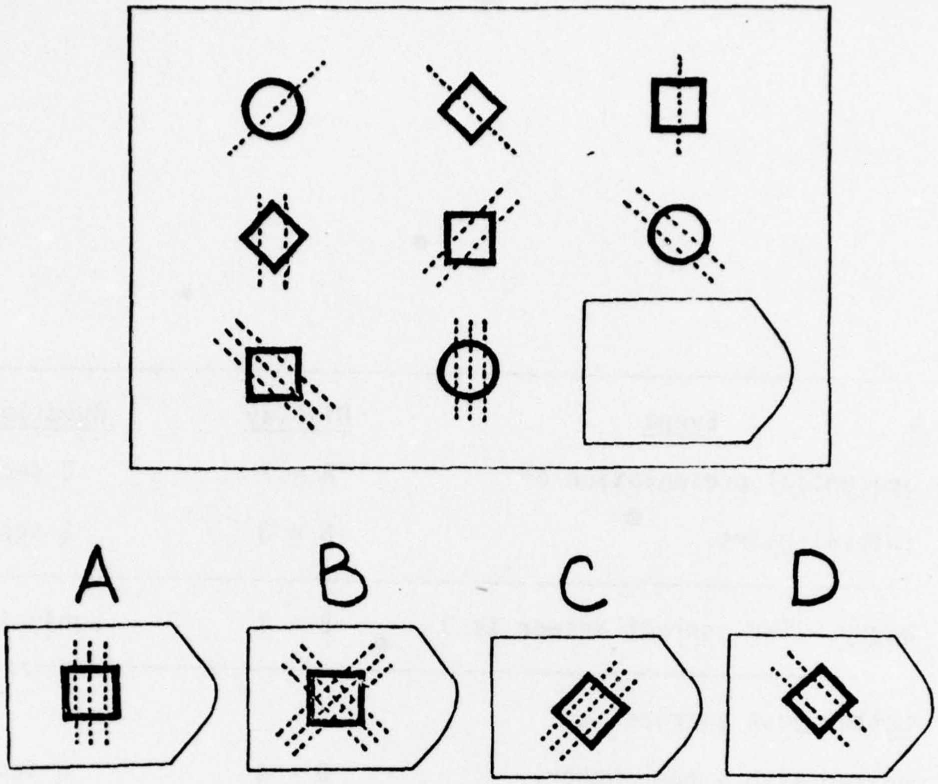
MEAN VERIFICATION RT (MSEC)
1600
1500
1400
1300
1200
1100
1000
900
800
700
600
500
WELL FIT
(n = 21)
POORLY FIT
(n = 11)
K
(TA)
K+1
(FA)
K+4
(FN)
K+5
(TN)
HYPOTHESIZED NUMBER OF CONSTITUENT COMPARISONS

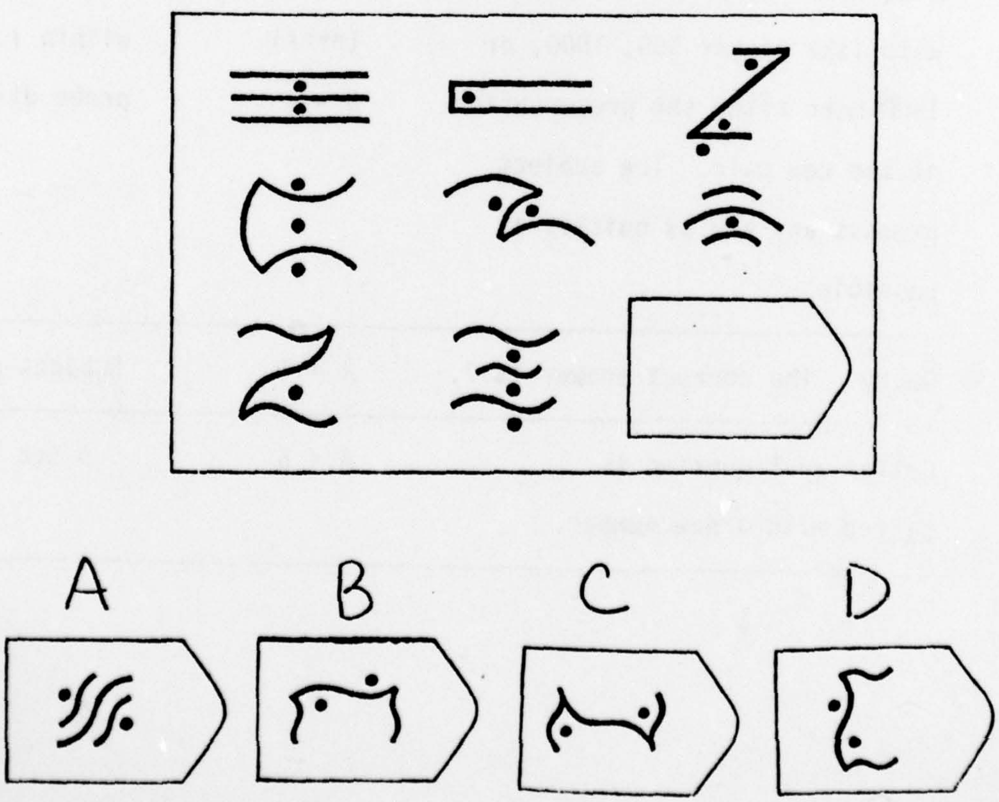

1600
1500
1400
1300
1200
1100
1000
900
800
700
600
500
400
LINGUISTIC
FREE
SPATIAL
TA
(k)
FA
(k+1)
FN
(k+4)
TN
(k+5)
HYPOTHESIZED NUMBER OF CONSTITUENT COMPARISONS

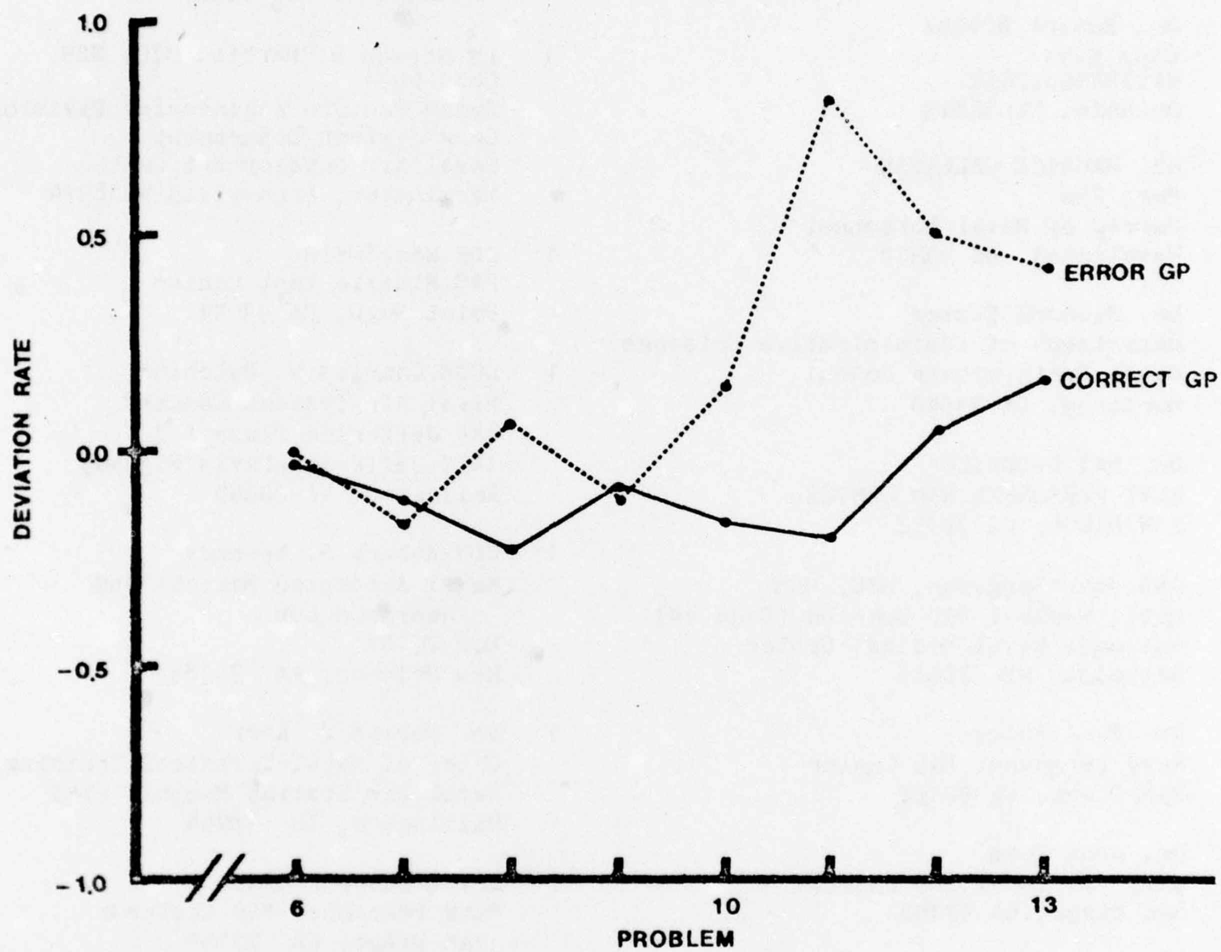


A SHOCKINGLY SIMPLE MODEL OF THINKING

Event	Display	Duration
Sequential presentation of initial pairs.	A = 7 B = 3	3 sec 3 sec
Query. The correct answer is 3.	B = ?	Subject-paced
Letter just queried is paired with a new number.	B = 4	3 sec
(Visual probe: On 3/4 of the trials in the probe condition, asterisks appear 500, 1000, or 1500 msec after the presentation of the new pair. The subject presses any key as quickly as possible.	(****) B = 4	(If subject fails to respond to probe within 1.5 sec, the probe disappears.)
Query. The correct answer is 7.	A = ?	Subject-paced
Letter just queried is paired with a new number.	A = 5	3 sec


A
B
C
D


A
B
C
D



1.0
0.5
0.0
-0.5
-1.0
DEVIATION RATE
6
10
13
PROBLEM
ERROR GP
CORRECT GP

Navy

1 Dr. Ed Aiken
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Robert Breaux
Code N-71
NAVTRAEQUIPCEN
Orlando, FL 32813

1 MR. MAURICE CALLAHAN
Pers 23a
Bureau of Naval Personnel
Washington, DC 20370

1 Dr. Richard Elster
Department of Administrative Sciences
Naval Postgraduate School
Monterey, CA 93940

1 DR. PAT FEDERICO
NAVY PERSONNEL R&D CENTER
SAN DIEGO, CA 92152

1 CDR John Ferguson, MSC, USN
Naval Medical R&D Command (Code 44)
National Naval Medical Center
Bethesda, MD 20014

1 Dr. Paul Foley
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. John Ford
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Richard Gibson
Bureau of Medecine and Surgery
Code 513
Navy Department
Washington, DC 20372

CAPT. D.M. GRAGG, MC, USN
HEAD, SECTION ON MEDICAL EDUCATION
UNIFORMED SERVICES UNIV. OF THE
HEALTH SCIENCES
6917 ARLINGTON ROAD
BETHESDA, MD 20014

Navy

1 MR. GEORGE N. GRAINE
NAVAL SEA SYSTEMS COMMAND
SEA 047C112
WASHINGTON, DC 20362

1 LT Steven D. Harris, MSC, USN
Code 6041
Human Factors Engineering Division
Crew Systems Department
Naval Air Development Center
Warminster, Pennsylvania 18974

1 CDR Wade Helm
PAC Missile Test Center
Point Mugu, CA 93041

1 LCDR Charles W. Hutchins
Naval Air Systems Command
444 Jefferson Plaza # 1
1411 Jefferson Davis Highway
Arlington, VA 20360

1 CDR Robert S. Kennedy
Naval Aerospace Medical and
Research Lab
Box 29407
New Orleans, LA 70189

1 Dr. Norman J. Kerr
Chief of Naval Technical Training
Naval Air Station Memphis (75)
Millington, TN 38054

1 Dr. Leonard Kroeker
Navy Personnel R&D Center
San Diego, CA 92152

1 CHAIRMAN, LEADERSHIP & LAW DEPT.
DIV. OF PROFESSIONAL DEVELOPMMENT
U.S. NAVAL ACADEMYY
ANNAPOLIS, MD 21402

1 Dr. William L. Maloy
Principal Civilian Advisor for
Education and Training
Naval Training Command, Code 00A
Pensacola, FL 32508

Navy

1 CAPT Richard L. Martin
USS Francis Marion (LPA-249)
FPO New York, NY 09501

2 Dr. James McGrath
Navy Personnel R&D Center
Code 306
San Diego, CA 92152

1 DR. WILLIAM MONTAGUE
LRDC
UNIVERSITY OF PITTSBURGH
3939 O'HARA STREET
PITTSBURGH, PA 15213

1 Commanding Officer
U.S. Naval Amphibious School
Coronado, CA 92155

1 Commanding Officer
Naval Health Research
Center
Attn: Library
San Diego, CA 92152

1 Naval Medical R&D Command
Code 44
National Naval Medical Center
Bethesda, MD 20014

1 CAPT Paul Nelson, USN
Chief, Medical Service Corps
Code 7
Bureau of Medicine & Surgery
U. S. Department of the Navy
Washington, DC 20372

1 Library
Navy Personnel R&D Center
San Diego, CA 92152

Technical Director
Navy Personnel R&D Center
San Diego, CA 92152

6 Commanding Officer
Naval Research Laboratory
Code 2627
Washington, DC 20390

Navy

1 JOHN OLSEN
CHIEF OF NAVAL EDUCATION &
TRAINING SUPPORT
PENSACOLA, FL 32509

1 Psychologist
ONR Branch Office
495 Summer Street
Boston, MA 02210

1 Psychologist
ONR Branch Office
536 S. Clark Street
Chicago, IL 60605

1 Office of Naval Research
Code 200
Arlington, VA 22217

1 Office of Naval Research
Code 437
800 N. Quincy SStreet
Arlington, VA 22217

1 Office of Naval Research
Code 441
800 N. Quincy Street
Arlington, VA 22217

5 Personnel & Training Research Programs
(Code 458)
Office of Naval Research
Arlington, VA 22217

1 Psychologist
OFFICE OF NAVAL RESEARCH BRANCH
223 OLD MARYLEBONE ROAD
LONDON, NW, 15TH ENGLAND

1 Psychologist
ONR Branch Office
1030 East Green Street
Pasadena, CA 91101

1 Scientific Director
Office of Naval Research
Scientific Liaison Group/Tokyo
American Embassy
APO San Francisco, CA 96503

Navy

1 Office of the Chief of Naval Operations
Research, Development, and Studies Branc
(OP-102)
Washington, DC 20350

1 Assistant Chief of Naval Personnel
for Human Resource Managment
(Pers-6)
U. S. Department of the Navy
Washington, DC 20370

1 Scientific Advisor to the Chief of
Naval Personnel (Pers-Or)
Naval Bureau of Personnel
Room 4410, Arlington Annex
Washington, DC 20370

1 LT Frank C. Petho, MSC, USNR (Ph.D)
Code L51
Naval Aerospace Medical Research Laborat
Pensacola, FL 32508

1 DR. RICHARD A. POLLAK
ACADEMIC COMPUTING CENTER
U.S. NAVAL ACADEMY
ANNAPOLIS, MD 21402

1 Roger W. Remington, Ph.D
Code L52
NAMRL
Pensacola, FL 32508

1 Dr. Bernard Rimland
Navy Personnel R&D Center
San Diego, CA 92152

1 Mr. Arnold Rubenstein
Naval Personnel Support Technology
Naval Material Command (08T244)
Room 1044, Crystal Plaza #5
2221 Jefferson Davis Highway
Arlington, VA 20360

1 Dr. Worth Scanland
Chief of Naval Education and Training
Code N-5
NAS, Pensacola, FL 32508

Navy

1 A. A. SJOHOLM
TECH. SUPPORT, CODE 201
NAVY PERSONNEL R& D CENTER
SAN DIEGO, CA 92152

1 Mr. Robert Smith
Office of Chief of Naval Operations
OP-987E
Washington, DC 20350

1 Dr. Alfred F. Smode
Training Analysis & Evaluation Group
(TAEG)
Dept. of the Navy
Orlando, FL 32813

1 Dr. Richard Sorensen
Navy Personnel R&D Center
San Diego, CA 92152

1 CDR Charles J. Theisen, JR. MSC, USN
Head Human Factors Engineering Div.
Naval Air Development Center
Warminster, PA 18974

1 W. Gary Thomson
Naval Ocean Systems Center
Code 7132
San Diego, CA 92152

1 DR. MARTIN F. WISKOFF
NAVY PERSONNEL R& D CENTER
SAN DIEGO, CA 92152

Army

1 HQ USAREUE & 7th Army
ODCSOPS
USAAREUE Director of GED
APO New York 09403

1 DR. RALPH CANTER
U.S. ARMY RESEARCH INSTITUTE
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333

1 DR. RALPH DUSEK
U.S. ARMY RESEARCH INSTITUTE
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333

1 Dr. Ed Johnson
Army Research Institute
5001 Eisenhower Blvd.
Alexandria, VA 22333

1 Dr. Michael Kaplan
U.S. ARMY RESEARCH INSTITUTE
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333

1 Dr. Milton S. Katz
Individual Training & Skill
Evaluation Technical Area
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Beatrice J. Farr
Army Research Institute (PERI-OK)
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Harold F. O'Neil, Jr.
ATTN: PERI-OK
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333

1 Director, Training Development
U.S. Army Administration Center
ATTN: Dr. Snerrill
Ft. Benjamin Harrison, IN 46218

Army

1 Dr. Joseph Ward
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Air Force

1 DR. G. A. ECKSTRAND
AFHRL/AS
WRIGHT-PATTERSON AFB, OH 45433

1 CDR. MERCER
CNET LIAISON OFFICER
AFHRL/FLYING TRAINING DIV.
WILLIAMS AFB, AZ 85224

1 Research Branch
AFMPC/DPMYP
Randolph AFB, TX 78148

1 Dr. Marty Rockway (AFHRL/TT)
Lowry AFB
Colorado 80230

1 Jack A. Thorpe, Capt, USAF
Program Manager
Life Sciences Directorate
AFOSR
Bolling AFB, DC 20332

1 Brian K. Waters, LCOL, USAF
Air University
Maxwell AFB
Montgomery, AL 36112

Marines

1 Director, Office of Manpower Utilization
HQ, Marine Corps (MPU)
BCB, Bldg. 2009
Quantico, VA 22134

1 DR. A.L. SLAFKOSKY
SCIENTIFIC ADVISOR (CODE RD-1)
HQ, U.S. MARINE CORPS
WASHINGTON, DC 20380

CoastGuard

Mr. Richard Lanterman
PSYCHOLOGICAL RESEARCH (G-P-1/62)
U.S. COAST GUARD HQ
WASHINGTON, DC 20590

Other DoD

1 Dr. Stephen Andriole
ADVANCED RESEARCH PROJECTS AGENCY
1400 WILSON BLVD.
ARLINGTON, VA 22209

12 Defense Documentation Center
Cameron Station, Bldg. 5
Alexandria, VA 22314
Attn: TC

1 Dr. Dexter Fletcher
ADVANCED RESEARCH PROJECTS AGENCY
1400 WILSON BLVD.
ARLINGTON, VA 22209

1 Military Assistant for Training and Personnel Technology
Office of the Under Secretary of Defense for Research & Engineering
Room 3D129, The Pentagon
Washington, DC 20301

Civil Govt

1 Dr. Susan Chipman
Basic Skills Program
National Institute of Education
1200 19th Street NW
Washington, DC 20208

1 Dr. Richards J. Heuer
ORPA/AMERS
Washington, DC 20505

1 Dr. Joseph I. Lipson
Division of Science Education
Room W-638
National Science Foundation
Washington, DC 20550

1 Dr. Joseph Markowitz
Office of Research and Development
Central Intelligence Agency
Washington, DC 20205

1 Dr. John Mays
National Institute of Education
1200 19th Street NW
Washington, DC 20208

1 Dr. Arthur Melmed
National Intitute of Education
1200 19th Street NW
Washington, DC 20208

1 Dr. H. Wallace Sinaiko
Program Director
Manpower Research and Advisory Services
Smithsonian Institution
801 North Pitt Street
Alexandria, VA 22314

1 Dr. Thomas G. Sticht
Basic Skills Program
National Institute of Education
1200 19th Street NW
Washington, DC 20208

1 Dr. Joseph L. Young, Director
Memory & Cognitive Processes
National Science Foundation
Washington, DC 20550

Non Govt

1 Dr. Earl A. Alluisi
HQ, AFHRL (AFSC)
Brooks AFB, TX 78235

1 Dr. John R. Anderson
Department of Psychology
Carnegie Mellon University
Pittsburgh, PA 15213

1 DR. MICHAEL ATWOOD
SCIENCE APPLICATIONS INSTITUTE
40 DENVER TECH. CENTER WEST
7935 E. PRENTICE AVENUE
ENGLEWOOD, CO 80110

1 1 psychological research unit
Dept. of Defense (Army Office)
Campbell Park Offices
Canberra ACT 2600, Australia

1 Dr. Alan Baddeley
Medical Research Council
Applied Psychology Unit
15 Chaucer Road
Cambridge CB2 2EF
ENGLAND

1 Dr. Nicholas A. Bond
Dept. of Psychology
Sacramento State College
600 Jay Street
Sacramento, CA 95819

1 Dr. Lyle Bourne
Department of Psychology
University of Colorado
Boulder, CO 80302

1 Dr. John S. Brown
XEROX Palo Alto Research Center
3333 Coyote Road
Palo Alto, CA 94304

1 DR. C. VICTOR BUNDERSON
WICAT INC.
UNIVERSITY PLAZA, SUITE 10
1160 SO. STATE ST.
OREM, UT 84057

Non Govt

1 Dr. John B. Carroll
Psychometric Lab
Univ. of No. Carolina
Davie Hall 013A
Chapel Hill, NC 27514

1 Charles Myers Library
Livingstone House
Livingstone Road
Stratford
London E15 2LJ
ENGLAND

1 Dr. William Chase
Department of Psychology
Carnegie Mellon University
Pittsburgh, PA 15213

1 Dr. Micheline Chi
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

1 Dr. John Chiorini
Litton-Mellonics
Box 1286
Springfield, VA 22151

1 Dr. Meredith Crawford
Department of Engineering Administration
George Washington University
Suite 805
2101 L Street N. W.
Washington, DC 20037

1 Mr. Ken Cross
Anacapa Sciences, Inc.
P.O. Drawer Q
Santa Barbara, CA 93102

1 Dr. Hubert Dreyfus
Department of Philosophy
University of California
Berkely, CA 94720

Non Govt

1 MAJOR I. N. EVONIC
CANADIAN FORCES PERS. APPLIED RESEARCH
1107 AVENUE ROAD
TORONTO, ONTARIO, CANADA

1 Dr. Ed Feigenbaum
Department of Computer Science
Stanford University
Stanford, CA 94305

1 Dr. Victor Fields
Dept. of Psychology
Montgomery College
Rockville, MD 20850

1 Dr. Edwin A. Fleishman
Advanced Research Resources Organ.
Suite 900
4330 East West Highway
Washington, DC 20014

1 Dr. John R. Frederiksen
Bolt Beranek & Newman
50 Moulton Street
Cambridge, MA 02138

1 Dr. Vernon S. Gerlach
College of Education
146 Payne Bldg. B
Arizona State University
Tempe, AZ 85281

1 DR. ROBERT GLASER
LRDC
UNIVERSITY OF PITTSBURGH
3939 O'HARA STREET
PITTSBURGH, PA 15213

1 DR. JAMES G. GREENO
LRDC
UNIVERSITY OF PITTSBURGH
3939 O'HARA STREET
PITTSBURGH, PA 15213

1 Dr. Barbara Hayes-Roth
The Rand Corporation
1700 Main Street
Santa Monica, CA 90406

Non Govt

1 Dr. Frederick Hayes-Roth
The Rand Corporation
1700 Main Street
Santa Monica, CA 90406

1 Dr. James R. Hoffman
Department of Psychology
University of Delaware
Newark, DE 19711

1 Dr. Lloyd Humphreys
Department of Psychology
University of Illinois
Champaign, IL 61820

1 Library
HumRRO/Western Division
27857 Berwick Drive
Carmel, CA 93921

1 Dr. Steven W. Keele
Dept. of Psychology
University of Oregon
Eugene, OR 97403

1 Dr. Walter Kintsch
Department of Psychology
University of Colorado
Boulder, CO 80302

1 Dr. David Kieras
Department of Psychology
University of Arizona
Tuscon, AZ 85721

1 Mr. Marlin Kroger
1117 Via Goleta
Palos Verdes Estates, CA 90274

1 LCOL. C.R.J. LAFLEUR
PERSONNEL APPLIED RESEARCH
NATIONAL DEFENSE HQS
101 COLONEL BY DRIVE
OTTAWA, CANADA K1A OK2

1 Dr. Alan Lesgold
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Non Govt

1 Dr. Robert R. Mackie
Human Factors Research, Inc.
6780 Cortona Drive
Santa Barbara Research Pk.
Goleta, CA 93017

1 Dr. Richard B. Millward
Dept. of Psychology
Hunter Lab.
Brown University
Providence, RI 82912

1 Richard T. Mowday
College of Business Administration
University of Oregon
Eugene, OR 97403

1 Dr. Allen Munro
Univ. of So. California
Behavioral Technology Labs
3717 South Hope Street
Los Angeles, CA 90007

1 Dr. Donald A Norman
Dept. of Psychology C-009
Univ. of California, San Diego
La Jolla, CA 92093

1 Dr. Melvin R. Novick
Iowa Testing Programs
University of Iowa
Iowa City, IA 52242

1 Dr. Jesse Orlansky
Institute for Defense Analysis
400 Army Navy Drive
Arlington, VA 22202

1 Dr. Robert Pachella
Department of Psychology
Human Performance Center
330 Packard Road
Ann Arbor, MI 48104

1 Mr. A. J. Pesch, President
Eclectech Associates, Inc.
P. O. Box 178
N. Stonington, CT 06359

Non Govt

MR. LUIGI PETRULLO
2431 N. EDGEWOOD STREET
ARLINGTON, VA 22207

DR. PETER POLSON
DEPT. OF PSYCHOLOGY
UNIVERSITY OF COLORADO
BOULDER, CO 80302

DR. DIANE M. RAMSEY-KLEE
R-K RESEARCH & SYSTEM DESIGN
3947 RIDGEMONT DRIVE
MALIBU, CA 90265

Dr. Peter B. Read
Social Science Research Council
605 Third Avenue
New York, NY 10016

Dr. Fred Reif
SESAME
c/o Physics Department
University of California
Berkely, CA 94720

Dr. Andrew M. Rose
American Institutes for Research
1055 Thomas Jefferson St. NW
Washington, DC 20007

Dr. Ernst Z. Rothkopf
Bell Laboratories
600 Mountain Avenue
Murray Hill, NJ 07974

Dr. David Rumelhart
Center for Human Information Processing
Univ. of California, San Diego
La Jolla, CA 92093

Dr. Irwin Sarason
Department of Psychology
University of Washington
Seattle, WA 98195

DR. WALTER SCHNEIDER
DEPT. OF PSYCHOLOGY
UNIVERSITY OF ILLINOIS
CHAMPAIGN, IL 61820

Non Govt

1 DR. ROBERT J. SEIDEL
INSTRUCTIONAL TECHNOLOGY GROUP
HUMRRO
300 N. WASHINGTON ST.
ALEXANDRIA, VA 22314

1 Dr. Richard Snow
School of Education
Stanford University
Stanford, CA 94305

1 Dr. Robert Sternberg
Dept. of Psychology
Yale University
Box 11A, Yale Station
New Haven, CT 06520

1 DR. PATRICK SUPPES
INSTITUTE FOR MATHEMATICAL STUDIES IN THE SOCIAL SCIENCES
STANFORD UNIVERSITY
STANFORD, CA 94305

1 DR. PERRY THORNDYKE
THE RAND CORPORATION
1700 MAIN STREET
SANTA MONICA, CA 90406

1 Dr. Douglas Towne
Univ. of So. California
Behavioral Technology Labs
3717 South Hope Street
Los Angeles, CA 90007

1 Dr. J. Uhlaner
Perceptronics, Inc.
6271 Variel Avenue
Woodland Hills, CA 91364

1 Dr. Benton J. Underwood
Dept. of Psychology
Northwestern University
Evanston, IL 60201

1 Dr. David J. Weiss
N660 Elliott Hall
University of Minnesota
75 E. River Road
Minneapolis, MN 55455

1 Dr. Karl Zinn
Center for Research on Learning and Teaching
University of Michigan
Ann ARbor, Michigan